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A Feasibility Study on Using Physics-Based Modeler Outputs to Train Probabilistic Neural Networks for UXO Classification

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13. ABSTRACT *(Maximum 200 words)*
A probabilistic neural network (PNN) has been applied to the detection and classification of unexploded ordnance (UXO) measured using magnetometry data collected using the Multi-sensor Towed Array Detection System (MTADS). Physical parameters obtained from a physics-based modeler were used to describe the UXO and scrap targets found at three sites: Badlands Bombing Range (BBR) Target 1 and 2 and the Former Buckley Field. The PNN was trained and tested using cross-validation (CV) software developed at NRL. The PNN was able to correctly identify between 84 % to 94 % of the targets. By adjusting the probability threshold, further improvements in the discrimination of UXO were possible: 96 % of the UXO were correctly identified for BBR Target 1, 100% for BBR Target 2, and 94 % for the former Buckley Field. The ability to train using one site (BBR target 2) and predict another (BBR Target 1) was successful with 95 % of the UXO correctly identified and a false alarm rate of 35%.

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EXECUTIVE SUMMARY

This study has demonstrated that it is possible to use the outputs from a physics-based modeler (magnetometry data only) for training a probabilistic neural network (PNN) to discriminate UXO from scrap. As expected, classification performance was found to be data set dependent. The PNN classification performance tracked the visual clustering of the data seen using principal component analysis and nonlinear mapping (i.e., good clustering = good classification performance). Model outputs from BBR2 were used to train a PNN model, which could correctly discriminate UXO from scrap at the BBR1 location. The exact cause for many of the misclassified UXO could not be determined from the results in this study, although most of the misclassifications occurred for small ordnance. The model outputs for the misclassified objects were much different than the outputs for the others in that UXO class. Further improvements in the modeler or the use of data fusion of MAG and EM responses must be made in order for classification results to improve.

INTRODUCTION

Locating, identifying and disposing of buried UXO on the 10 million acres of contaminated lands in the continental United States is a 500 billion dollar problem. Development of new technologies with improved data analysis has been identified as a high priority triservice requirement. Using current methods, it has been shown that false alarm detections far outnumber correctly identified ordnance. The best performing technologies typically have a false alarm rate of 300-500%.[1, 2, 3, 4] The high cost of digging and disposing of targets accounts for the overwhelming portion of the costs of UXO remediation, therefore a substantial saving could be recognized if the number of false positives were reduced. Using data collected by the Naval Research Laboratory's Multi-sensor Towed Array Detection System (*MTADS*), new software techniques are being developed to improve discrimination and reduce the false alarm rate. The program has three parts: Phase 1, Target Detection, Phase 2, Quantitative Modeling, and Phase 3, Target Classification. This paper describes the first stages of Phase 3, Target Classification.

A feasibility study on using a physics-based modeler to generate inputs for a probabilistic neural network (PNN) for UXO classification has been completed. Magnetometer survey data taken at three field sites using the *MTADS* were used. The physics-based modeler (point-dipole model) used in the *MTADS*-DAS (*MTADS*-Data Analysis System) estimates the object's depth (dep), size (siz), inclination (inc), magnetic moment (mom), azimuth (azi), and also returns a modeler fit quality (fit). The modeler parameters dep, mom, inc, and azi are independent variables while siz is a dependent variable. The parameter fit is neither and reflects how well the modeler was able to describe the target item in question. A new modeler based on oblate spheroids is being developed in Phase 2 of this program to improve shape discrimination. The new modeler was not available for this feasibility study. In the current *MTADS*-DAS, a trained analyst performs classification using both visual clues and the modeler outputs as a guide. The analyst also uses knowledge of site use history and ground truth. This process can be slow and tedious even for an expert analyst working with large data sets. In order to expedite this process, we are studying the feasibility of using a PNN to automate the UXO discrimination task.

In this study, the discrimination of ordnance from ordnance scrap items and other clutter for three different locations was performed using the PNN. After evaluating the initial classification results, the data sets were characterized and several strategies were investigated to improve the performance of the PNN on these data sets. Recommendations are then given for further research in this area.

EXPERIMENTAL

Outputs from the physics-based modeler and associated dig sheets were received in Microsoft Excel spreadsheets and read into Matlab (Version 5.2, Mathworks, Inc., Natick, MA) as a tab-delimited text file. These model outputs are given in Tables 7,[5] 10, and 11.[6] Prior to PNN training, the raw model outputs were autoscaled (columns with a mean of zero and unit variance). The PNN software and nonlinear mapping routines were written by the authors in Matlab. Principal Component Analysis (PCA) was

implemented using the PLS_toolbox, version 2.0c (Eigenvector Technologies, Inc., Manson, WA).

The factors that describe the major trends in the data can be evaluated through PCA. One of the most useful first steps in multivariate analysis is to observe the clustering of the data in the multi-dimensional space. Because it is impossible to visualize the data points clustering in n-dimensional space, display, mapping and cluster analyses are used. An exploratory algorithm was used in this study to provide an interpretable view of the multi-dimensional data space. Principal Component Analysis (PCA),[7] also known as the Karhunen-Loeve transformation, is a display method that transforms the data into two- and three-dimensional space for easier visualization. PCA finds the axes in the data space that account for the major portion of the variance while maintaining the least amount of error. PCA finds the linear combinations of variables or sensors that describe the major trends in the data. The first principal component captures the largest amount of information or variance in the data. The best plane that represents the data space is achieved by plotting the first two principal components.

Mathematically, PCA computes a variance-covariance matrix for the stored data set and extracts the eigenvalues and eigenvectors. PCA decomposes the data matrix as the sum of the outer product vector, referred to as loadings and scores. The scores contain information on how the targets are related to each other and the loadings contain information on how the variables or model outputs relate to each other. Examination of the results of these methods provides insight into the data set. Non-linear mapping[8] is used to further improve the 2-dimensional display. This routine seeks to retain the distances between the data points in n-dimensional space in the 2-dimensional space by minimizing the mapping error.

Discrimination of UXO and clutter are being investigated in this program using multivariate classification methods. Classification methods are supervised learning techniques that use training sets to develop classification rules. The rules are used to predict classification of a future data set or site. These methods are given both the data and the correct classification results (i.e., "ground truth"), and they generate mathematical functions to define the classes. The best classification algorithms are those that provide the best prediction.

The PNN method[9, 10] was used in this study because it provides a probability that the target class is present and the level of confidence can be adjusted according to the ultimate land use requirements. Probabilistic Neural Networks are a class of neural networks that combine some of the best attributes of statistical pattern recognition methods and feed-forward neural networks.[11, 12] They have been described as the neural network implementation of kernel discriminant analysis and were first introduced into the neural network literature by Donald Specht in the late 1980's.[11] Initially developed for radar classification, the PNN has been used in a wide variety of applications including fingerprint identification[12], optical character recognition, remote sensing,[13] image processing,[14, 15] gas chromatography,[16] and chemical sensor arrays.[17]

Figure 1 shows the architecture of the PNN. The PNN is a nonlinear, nonparametric pattern recognition algorithm that operates by defining a probability density function (PDF) for each data class based on the training set data and the optimized kernel width parameter. For ordnance discrimination, the inputs are the physics-based modeler outputs or pattern vectors. The outputs are the Bayesian posterior probability (i.e., a measure of confidence in

the classification) that the input pattern vector is a member of one of the possible output classes, for example, UXO or scrap.

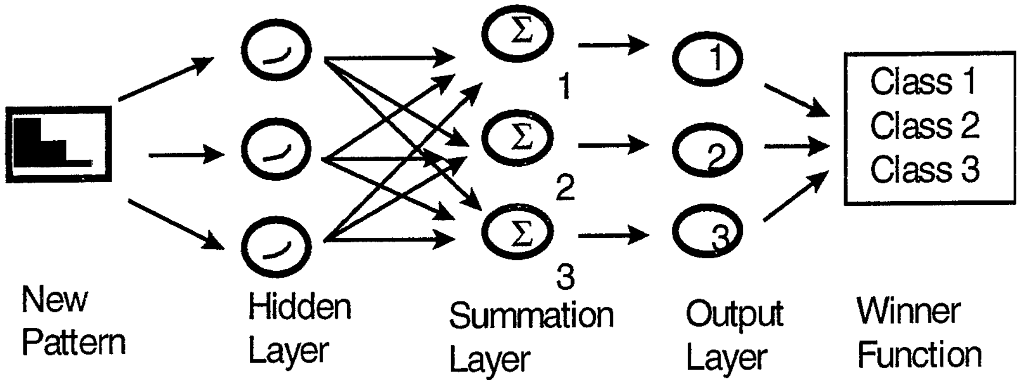

Figure 1. Topology of a PNN. Modeler outputs are used as input and the probability of belonging to one of the specified classes is determined

The hidden layer of the PNN is the heart of the algorithm. During the training phase, the pattern vectors in the training set are simply copied to the hidden layer of the PNN. Unlike other types of artificial neural networks, the basic PNN only has a single adjustable parameter. This parameter, termed sigma (σ), or kernel width, along with the members of the training set, define the PDF for each data class. In a PNN, each PDF is composed of Gaussian-shaped kernels of width σ located at each pattern vector. The PDF essentially determines the boundaries for classification. The kernel width is critical because it determines the amount of interpolation that occurs between adjacent pattern vectors. As the kernel width approaches zero, the PNN essentially reduces to a nearest neighbor classifier. This point is illustrated by the contour plot in Figure 2. These plots show four, two-dimensional pattern vectors for two classes (A and B). The PDF for each class is shown as the circles of decreasing intensity. The probability that a pattern vector will be classified as a member of a given output data class increases the closer it is to the center of the PDF for that class. In this example, any pattern vectors that occur inside the inner-most circle for each class would be classified with nearly 100% certainty. As σ is decreased (upper plot), the PDF for each class shrinks. For very small kernel widths, the PDF consists of groups of small circles scattered throughout the data space. A large kernel width (lower plot) has the advantage of producing a smooth PDF and good interpolation properties for predicting new pattern vectors. Small kernel widths reduce the amount of overlap between adjacent data classes. The optimized kernel width must strike a balance between a σ that is too large or too small.

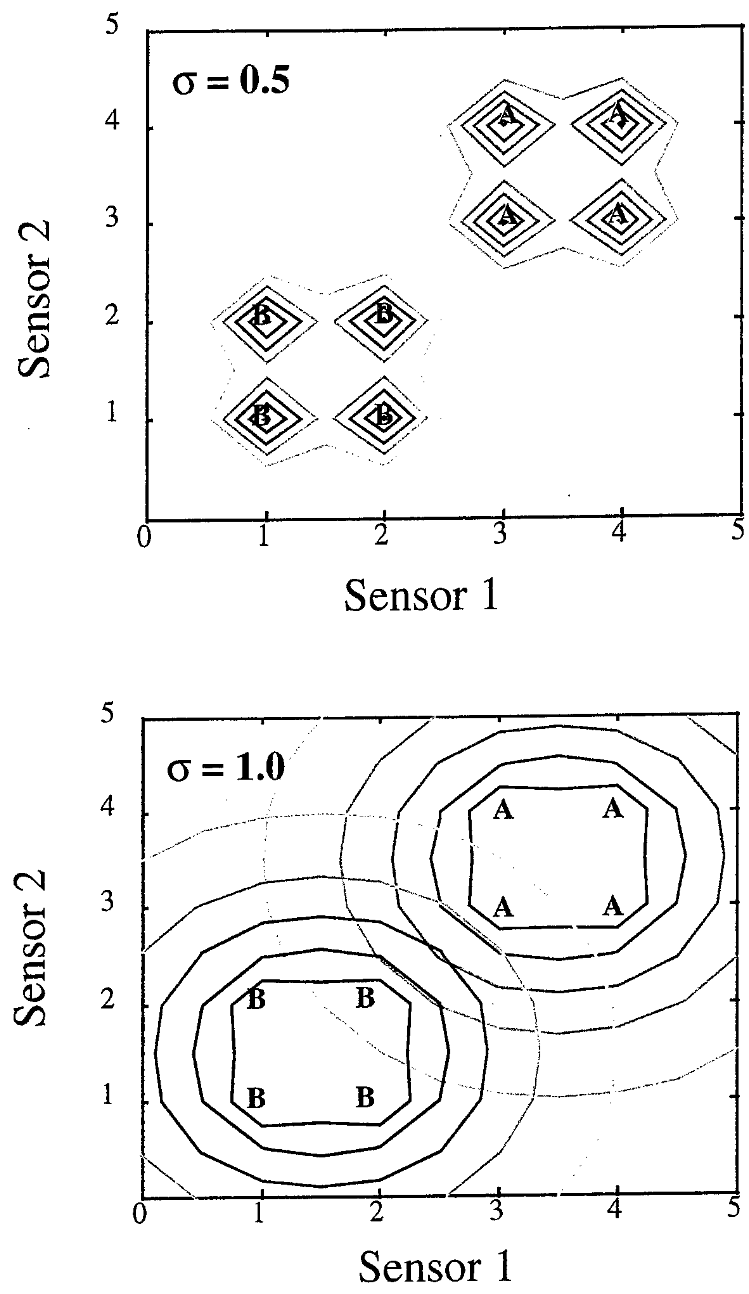

Figure 2. Contour plot illustrating the PDF for each class. Two classes are shown, A and B. Four events of each type are presented. The PDF for each class is shown as circles of decreasing intensity

Prediction of new targets using a PNN is more complicated than the training step. Each member of the training set of pattern vectors (i.e., the patterns stored in the hidden layer of the PNN and their respective classifications), and the optimized kernel width are used during each prediction. As new pattern vectors are presented to the PNN for classification, they are serially propagated through the hidden layer by computing the Euclidean distance, d, between the new pattern and each pattern stored in the hidden layer. The Euclidean distance scores are then processed through a nonlinear transfer function (the Gaussian kernel):

$$\text{Hidden\_Neuron\_Output} = \exp(-(d)/\sigma^2) \qquad (1)$$

Because each pattern in the hidden layer is used during each prediction, the execution speed of the PNN is considerably slower than some other algorithms. The mass data storage requirements can also be quite large since every pattern in the hidden layer is needed for prediction.

The summation layer consists of one neuron for each output class and simply collects the outputs from all hidden neurons of each respective class. The products of the summation layer are forwarded to the output layer where the estimated probability of the new pattern being a member of each class is computed. In the PNN, the sum of the output probabilities equals 100%. Using the model outputs as the input training set, PNNs were trained to perform the classification. One of the main advantages associated with using a PNN is the ability to output a probability for each of its classifications. For critical applications, such as ordnance detection and remediation, such an indicator of confidence is extremely useful in assisting the decision making process and reducing the likelihood that individual ordnance items are missed by reducing the detection probability.

As discussed above, the calculation of the optimum kernel width, σ, is imperative for high classification rates to be achieved. For the work described herein, an iterative algorithm for σ optimization was employed.[9] The algorithm was designed to minimize the following cross validation error:

$$error = N_m + \sum_{i=1}^{n}\left[(1-p_i)^2 + \sum_{i \neq j}(p_j)^2\right] \qquad (2)$$

where p_i is the predicted probability of being the correct class, p_j is the predicted probability of all the other classes, N_m is the number misclassified and n is the number of patterns in the training set. The minimization of Equation 2 is based upon a parabolic interpolation method described by Masters.[18]

RESULTS AND DISCUSSION

Badlands Bombing Range (BBR 1)

A subset of the Badlands data set, Bull's eye Target 1 (Pine Ridge Reservation, BBR 1) was investigated to determine the ability of a PNN to distinguish unexploded ordnance (UXO) from scrap. For PNN classification, the Badlands data set consisted of Magnetometer (MAG) model outputs from 87 buried objects that had been remediated. A 87×6 data matrix was formed where each row consisted of a set of model outputs for a target. The 6 columns are the parameters derived from the physics-based modeler. Each row represents a "pattern vector," using pattern recognition terminology. These pattern vectors were subdivided into two categories or classes: UXO and scrap. The UXO subset consisted of 44 distorted and intact M38 bombs, while the scrap subset primarily consisted of an assortment of bomb tail fins, dry holes, and other ordnance scrap totaling 43 targets. The PNN was used to discriminate the two classes of objects (i.e., differentiate UXO from scrap). This data set is limited in scope, representing a simple test case, as it contains only one type of UXO. Furthermore, much of the scrap is located near the surface while the bombs are generally found further below the surface. The parameters used in this work were derived from magnetometry data, which is different from the magnetometry and time-domain pulsed induction sensor joint inversion modeler data that will be used in the future. However, despite these limitations, the BBR 1 data set provides an excellent platform for determining the feasibility of using model outputs for PNN classification.

Data Set Characterization

An examination of the data set using PCA and non-linear mapping was undertaken to understand the clustering and overlap of the UXO classes and scrap in the data set. A plot of the first two factors, or principal components, for the BBR 1 data set is shown Figure 3. The classes are reasonably separated from one another, although there is some overlap and two UXO targets, 19 and 34 are located within the scrap cluster. A plot of the data in two dimensions generated by non-linear mapping is shown in Figure 4. An examination of Figure 4 reveals results similar to those in the PCA plot. In both plots, the scrap and M38 classes have some overlap (4 and 3 scrap targets found in the M38 data space for PCA and non-linear map plots respectively).

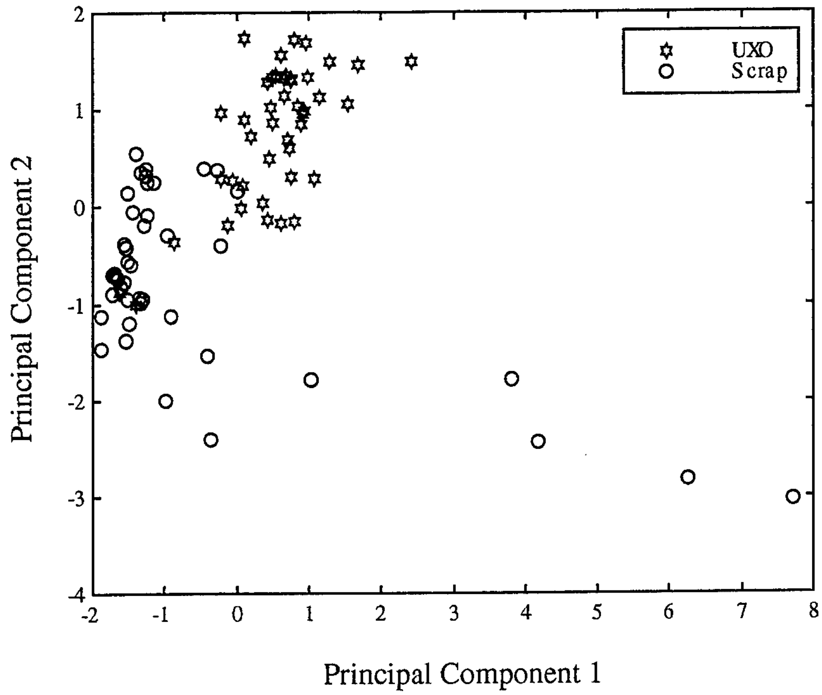

Figure 3. PCA scores plot of the BBR 1 data set. Two principal components account for 65.8 % of the variance

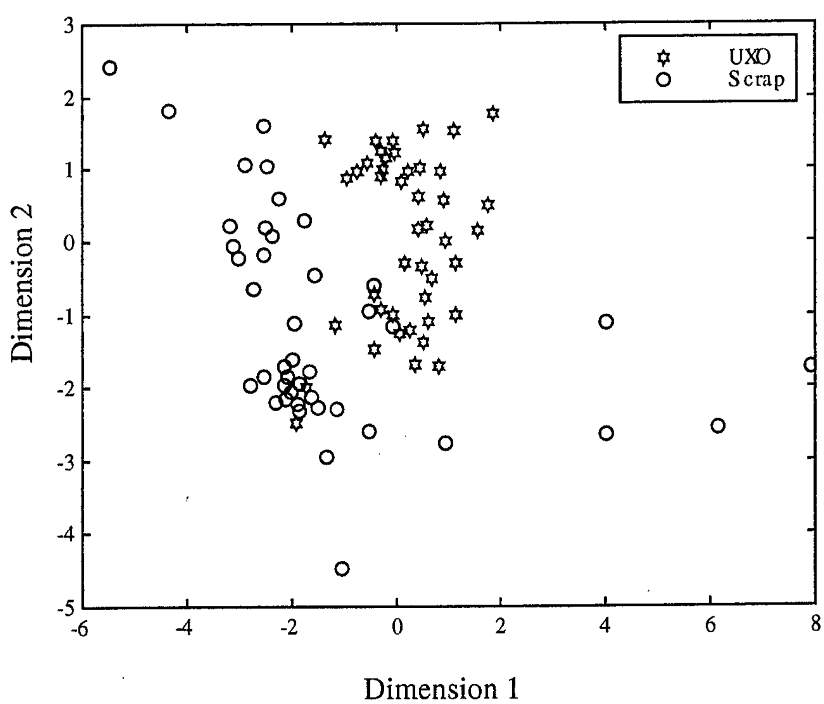

Figure 4. Non-linear map plot of the BBR 1 data set

Cross-Validation Performance

PNN classification performance was examined using leave-one-out-cross-validation (CV). Performance evaluation using cross-validation involves training the PNN using all the patterns in the data set except one, which is withheld for subsequent prediction. This process is repeated; leaving out each pattern in turn until all patterns have been used once in prediction. In general, CV is preferred to using a separate external validation or prediction set when only a small data set is available. In this work, the PNN returned two values for each pattern: the probability of being UXO and the probability of being scrap. Each pattern was assigned to the category having the highest probability. In a real-world scenario, this probability threshold can be adjusted for a particular site using *a priori* information regarding the types and relative number of buried objects, as well as the level of clearing desired for the ultimate land use requirements.

To determine which MAG model parameters were most important and to gain insight into the PNN classification, the effect of various model parameters were studied. PNN CV performance was determined for all possible combinations of one, two, three, four, five, and six MAG model parameters. Results from the single, five and six parameter patterns and representative results from the two, three, and four parameter patterns are given in Table 1. The UXO miss rate (missed detection) is defined as the

Table 1. ***MTADS*** **parameter combinations and PNN cross validation results for Badlands data**

Parameter Combination 1	2	3	4	5	6	UXO Miss Rate (%)[a]	False Alarm Rate (%)	# UXO Missed	# Scrap Missed
dep	-	-	-	-	-	11.4	9.3	5	4
-	siz	-	-	-	-	6.8	16.3	3	7
-	-	mom	-	-	-	9.1	9.3	4	4
-	-	-	inc	-	-	9.1	16.3	4	7
-	-	-	-	azi		0.0[b]	37.2	0[b]	16
-	-	-	-	-	fit	18.2	39.5	8	17
-	siz	-	inc	-	-	4.5	7.0	2	3
-	-	mom	inc	-	-	6.8	7.0	3	3
dep	-	-	inc	-	-	9.1	9.3	4	4
-	siz	mom	-	-	-	6.8	14.0	3	6
-	-	mom	-	-	fit	13.6	7.0	6	3
-	-	-	-	azi	fit	25.0	23.3	11	10
dep	siz	-	inc	-	-	4.5	7.0	2	3
-	siz	mom	inc	-	-	4.5	7.0	2	3
-	siz	-	inc	azi	-	4.5	7.0	2	3
-	-	-	inc	azi	fit	6.8	11.6	3	5
dep	siz	mom	-	-	-	6.8	14.0	3	6
-	-	mom	-	azi	fit	18.2	9.3	8	4
-	siz	-	inc	azi	fit	4.5	7.0	2	3
dep	siz	mom	inc	-	-	6.8	7.0	3	3
-	siz	mom	inc	azi	-	6.8	9.3	3	4
dep	siz	-	-	azi	fit	9.1	11.6	4	5
-	siz	mom	-	azi	fit	9.1	18.6	4	8
-	siz	mom	inc	azi	fit	6.8	7.0	3	3
dep	-	mom	inc	azi	fit	9.1	9.3	4	4
dep	siz	-	inc	azi	fit	6.8	7.0	3	3
dep	siz	mom	-	azi	fit	9.1	11.6	4	5
dep	siz	mom	inc	-	fit	6.8	9.3	3	4
dep	siz	mom	inc	azi	-	6.8	7.0	3	3
dep	siz	mom	inc	azi	fit	6.8	7.0	3	3

a Using a probability cut off of 50 %

b Favorable result is due to over training not intrinsic properties of the data and represents an anomaly

ratio of the number of UXO classified as scrap to the total number of UXO targets classified. The false alarm rate is defined as the ratio of the number of scrap classified as UXO to the total number of scrap classified.

The UXO miss rate and false alarm rate using all parameters were 6.8% and 7.0% respectively, corresponding to 3 UXO and 3 scrap targets missed. The parameters found to be most important (causing the greatest increase in UXO miss rate and false alarm rate when left out) in the tests using five parameter patterns were inc > siz > azi. The parameters, dep, mom, and fit had no effect on the performance when left out of the patterns.

The best single parameter for overall prediction was mom with a UXO miss rate of 9.1% and a false alarm rate of 9.3%. While mom did not negatively impact the classification performance of the PNN when left out of the input patterns, it was the best performing single parameter. This is due to the interdependence of the variables and PNN classification. Either inc or siz used alone produced generally poorer results: inc had a UXO miss rate of 9.1 % and a false alarm rate of 16.3 % and siz had a UXO miss rate of 6.8% and a false alarm rate of 16.3 %. The best UXO miss rate was obtained using siz alone at the expense of the false alarm rate. It should be noted that the favorable result using azi alone (UXO miss rate of 0%) is an anomaly related to network over-training and is not indicative of any intrinsic properties of this parameter. The false alarm rate using azi alone was 37.2 % indicating poor predictive capabilities. Finally, the use of fit alone resulted in the largest classification errors: 18.2 % and 39.5 % for the UXO miss rate and false alarm rate respectively.

The best classification results were obtained using only two parameters, siz and inc. This combination produced a UXO miss rate of 4.5 % and a false alarm rate of 7.0%, which corresponds to 2 UXO and 3 scrap targets missed or 94 % correct classification of the data set. These two parameters were also found to be the two most important in the five parameter pattern tests. Increasing the number of model parameters did not improve the performance. Figure 5 contains a plot of the PNN CV predicted probability of being UXO for each of the 87 patterns in the Badlands data sets using just two MAG parameters (siz and inc). The solid line represents the conventional 50% probability cut off threshold. As discussed above, the probability threshold can be adjusted in case *a priori* information is available or to reduce the number of missed detections. However, in this case, the two missed detections (objects 19 and 34) were predicted with very low probabilities of being UXO (< 10%). The misclassified targets were a distorted M38 (target 19) and a burster and fuse assembly (target 34). The three scrap items were a bomb fin (52), and two dry holes (62 and 63). These misclassifications occur because no other UXO patterns in the Badlands data set have similar MAG model outputs. In the eventual application of this technology, larger data sets comprised of UXO and scrap from many sites will be used to prevent this situation from occurring. The average probability of being UXO value of the correctly classified targets (UXO and scrap) and the outliers are found in Table 2.

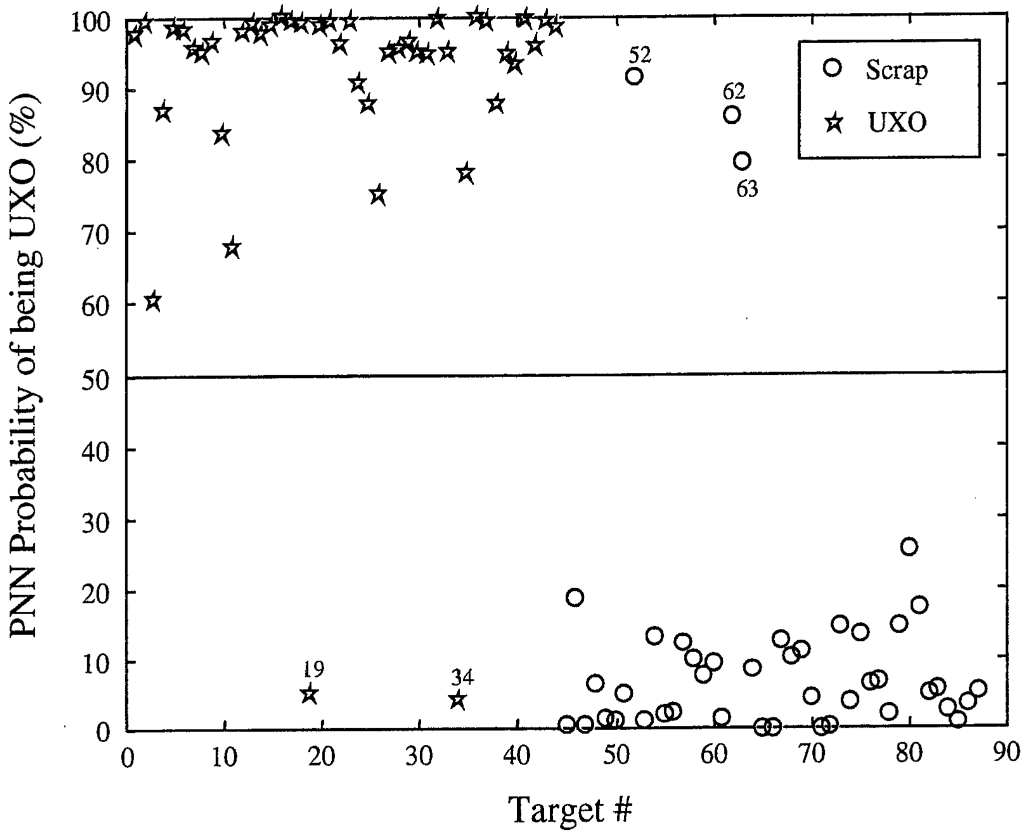

Figure 5. PNN probability of being UXO for badlands data determined using only siz and inc. The misclassified targets were 19: distorted M38, 34: M38 burster and fuse assembly, 52: bomb fin, 62: dry hole, 63: dry hole. The first 44 targets are UXO

Table 2. Probability of being UXO for correctly classified UXO, scrap and outliers in Figure 5

	Probability of being UXO
UXO	0.937 [a]
Scrap	0.067 [a]
19	0.051
34	0.041
52	0.915
62	0.860
63	0.794

[a] average of correctly classified targets

The complete performance characterization of the PNN for this dataset can be seen by examining a receiver operator characteristic (ROC) curve[19] shown in Figure 6. Each point in the ROC plot represents a different probability threshold at which the UXO detection rate and false alarm rates were calculated. The level of UXO classification required for the particular site in question can be selected and the corresponding false alarm rate for the PNN and site is given by the curve.

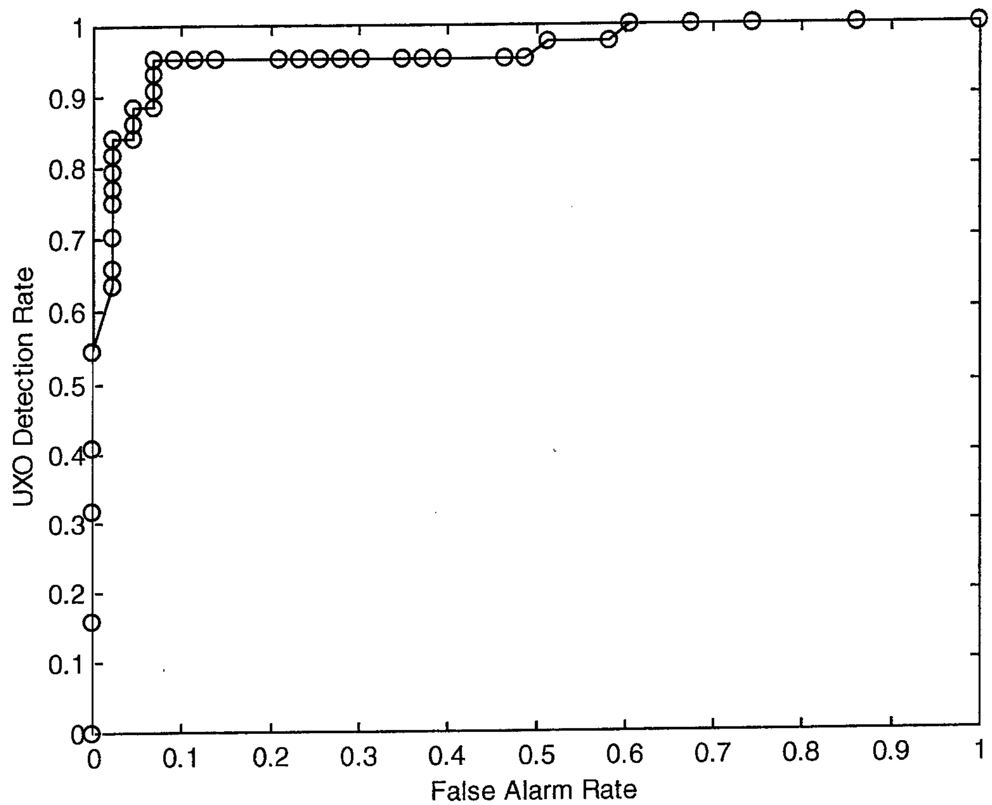

Figure 6. Receiver operator characteristic curve for BBR 1 using [dep siz inc]

An extensive examination of the effects of using different combinations of modeler output parameters on the classification performance of a PNN has been completed. The results obtained in this study are probably data set dependent and may vary according to the type of UXO and scrap encountered, the amount of scrap present, soil type, etc. However, at this location, only two or three parameters, [siz and inc] or [dep siz inc], were necessary to correctly classify all but 2 UXO and 3 scrap targets.

Badlands Bombing Range (BBR 2)

A second subset of the Badlands data set, Bull's eye Target 2 (Badland Bombing Range, BBR 2, Pine Ridge Reservation) was investigated to determine the ability of a PNN to distinguish UXO from scrap at a site containing more than one type of ordnance. For PNN classification, the BBR 2 data set tested contained MAG physics-based modeler outputs for 243 buried objects that had been remediated. A 243 $\times$ 6 data matrix was generated. Each row in the data matrix represents the model outputs for a target and is referred to as a pattern vector. For this study two approaches were investigated. In one case, these pattern vectors were subdivided into two categories or classes, UXO and Scrap for the data set classification labeled BBR 2 two-class problem. In the other case, the pattern vectors were subdivided into four classes for the data set classification labeled BBR 2 four-class problem. The UXO subsets of BBR 2 consisted of 14 2.75-inch Warheads (2.75 WH), 21 M38 bombs, 27 SCAR rockets (2.25-inch rockets), while the scrap subset (181 targets) contained a wide variety of items ranging from ordnance related scrap to fence wire. The data sets used for classification testing were prepared by selecting those targets with the descriptions listed above from the modeler output and truth tables for this site. The PNN was used to discriminate either two classes or four classes of objects (i.e., differentiate three UXO types from each other and scrap). The variability of the modeler parameters contributes to the difficulty in classification. The parameters used in this work were derived from MAG data, which is different from the MAG/EM joint inversion modeler data that will be used in the future. The BBR 2 data set represents a challenge to the PNN classification routines using modeler outputs for the discrimination of UXO from scrap.

Data Set Characterization

An examination of the data set using PCA and non-linear mapping was undertaken to understand the clustering and overlap of the UXO classes and scrap in the data set. A plot of the first two factors, or principal components, for the BBR 2 data set are shown Figure 7. Each of the UXO classes are reasonably separated from one another but there is significant overlap between the the 2.75 WH and SCAR UXO and the scrap items. The M38 bombs are separated from the other two UXO classes but more importantly are better separated from the scrap. A plot of the data in two dimensions generated by non-linear mapping is shown in Figure 8. An examination of Figure 8 reveals that the scrap class is heavily overlapped with the 2.75 WH and SCAR UXO classes while the M38 class is somewhat separated, similar to the PCA plot. In both the PCA and non-linear map plots, the SCAR and M38 UXO classes have some overlap (6 and 7 SCAR targets in the M38 data space for PCA and non-linear map plots respectively).

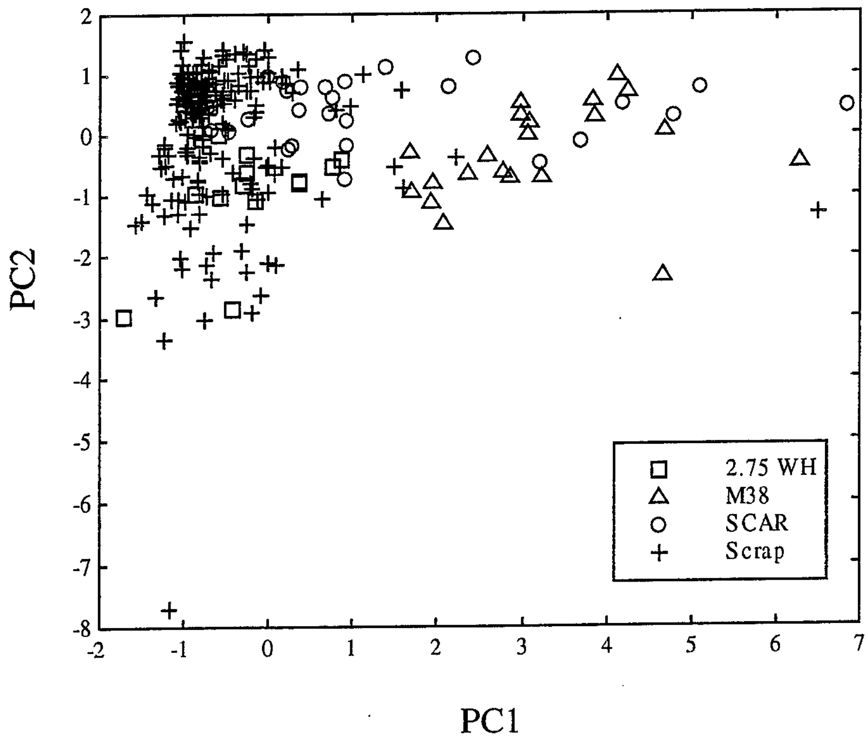

Figure 7. PCA scores plot of the BBR 2 data set. Two principal components account for 60.6 % of the variance

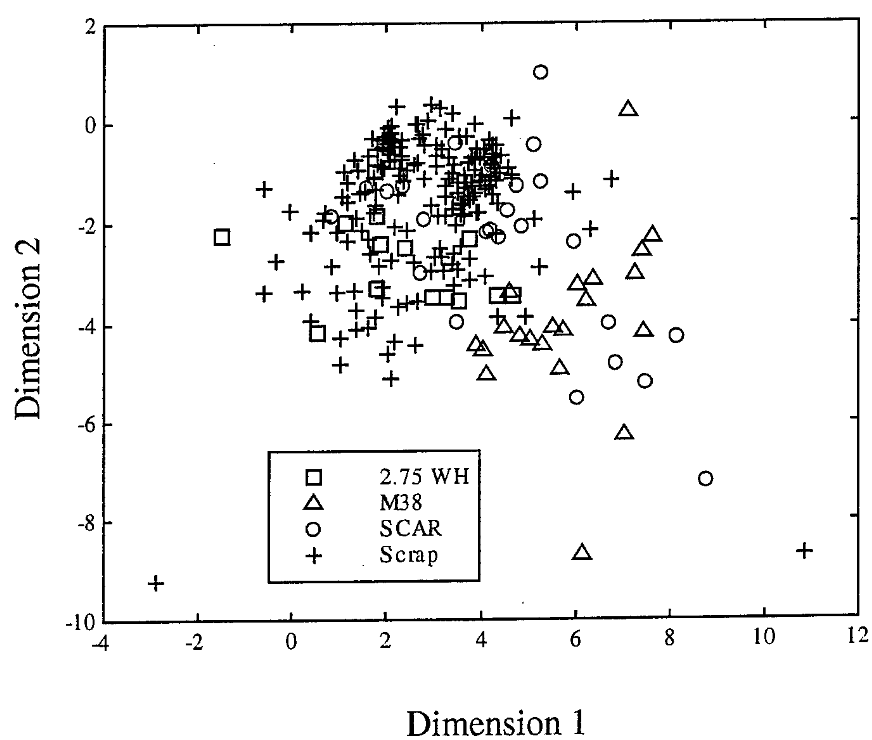

Figure 8. Non-linear map plot of the BBR 2 data set

Cross-Validation Performance

PNN classification performance was examined using leave-one-out-cross-validation (CV). In this work, the PNN returned either four or two values for each pattern: the probability of being one of the three UXO types and the probability of being scrap or simply UXO or scrap. Each pattern was assigned to the category having the highest probability. In a real-world scenario, this probability threshold can be adjusted for a particular site using *a priori* information regarding the types and relative number of buried objects.

To determine which MAG model parameters were most important and to gain insight into the PNN classification, the effect of various model parameters were studied. PNN CV performance was determined for all possible combinations of one, two, three, four, five, and six MAG model parameters. The UXO miss rate (missed detection) is defined as the ratio of the number of UXO classified as scrap to the total number of UXO targets classified. The false alarm rate is defined as the ratio of the number of scrap classified as UXO to the total number of scrap classified.

BBR 2 Classification (2 Class Problem)

The overall results from the single, five and six parameter patterns and representative results from the two, three, and four parameter patterns are given in Table 3 for a cutoff of 50%. The UXO miss rate and false alarm rate using all parameters were 37.1% and 4.4% respectively, corresponding to 23 UXO and 8 scrap targets missed.

The best single parameter for overall prediction was siz with a UXO miss rate of 30.6% and a false alarm rate of 8.8%. The use of fit alone resulted in the largest false alarm rate: 25.8% and 52.5% for the UXO miss rate and false alarm rate respectively. Using a four-parameter pattern containing dep, siz, mom, inc, the UXO miss rate was reduced to 24.2% and the false alarm rate was 9.9% for an overall correct classification of 86% of the data set. When mom is removed from this set, the overall performance is the same, while the number of missed UXO are reduced to 13 from 15. The best UXO detection was achieved with [siz inc azi]: 17.7 %, and 13.3 % for the UXO miss rate and false alarm rate respectively.

Table 3. Parameter combinations and PNN cross validation results for BBR 2 data set using 2 classes (UXO and Scrap) using a 50 % cutoff

Parameter Combination 1	2	3	4	5	6	UXO Miss Rate (%)	False Alarm Rate (%)	# UXO Missed	# Scrap Missed
dep	-	-	-	-	-	29.0	13.8	18	25
-	siz	-	-	-	-	30.6	8.8	19	16
-	-	mom	-	-	-	32.3	7.2	20	13
-	-	-	inc	-	-	33.9	30.9	21	56
-	-	-	-	azi		43.5	40.3	27	73
-	-	-	-	-	fit	25.8	52.5	16	95
-	siz	-	inc	-	-	33.9	6.1	21	11
-	-	mom	inc	-	-	43.5	7.2	27	13
dep	-	-	inc	-	-	29.0	16.0	18	29
-	siz	mom	-	-	-	32.3	7.2	20	13
-	-	mom	-	-	fit	40.3	4.4	25	8
-	-	-	-	azi	fit	22.6	57.5	14	104
dep	**siz**	**-**	**inc**	**-**	**-**	**21.0**	**11.6**	**13**	**21**
-	siz	mom	inc	-	-	35.5	5.5	22	10
-	**siz**	**-**	**inc**	**azi**	**-**	**17.7**	**13.3**	**11**	**24**
-	-	-	inc	azi	fit	37.1	31.5	23	57
dep	siz	mom	-	-	-	27.4	7.2	17	13
-	-	mom	-	azi	fit	48.4	3.3	30	6
-	siz	-	inc	azi	fit	21.0	13.8	13	25
dep	siz	mom	inc	-	-	24.2	9.9	15	18
-	**siz**	**mom**	**inc**	**azi**	**-**	**17.7**	**13.3**	**11**	**24**
dep	siz	-	inc	azi	-	29.0	9.4	18	17
-	siz	mom	-	azi	fit	38.7	6.6	24	12
-	**siz**	**mom**	**inc**	**azi**	**fit**	**19.4**	**13.3**	**12**	**24**
dep	-	mom	inc	azi	fit	27.4	11.6	17	21
dep	siz	-	inc	azi	fit	37.1	5.0	23	9
dep	siz	mom	-	azi	fit	29.0	7.2	18	13
dep	siz	mom	inc	-	fit	35.5	4.4	22	8
dep	siz	mom	inc	azi	-	29.0	9.4	18	17
dep	siz	mom	inc	azi	fit	37.1	4.4	23	8

The probability of being a UXO is shown in Figure 9 for all 243 targets in the BBR 2 data set. These probabilities were generated using the three-parameter combination found to produce the near best classification results: [dep siz inc], consistent with the other datasets. The majority of the UXO have a very high probability of being ordnance, while the majority of the scrap items have a very low probability of being ordnance. The upper solid, horizontal line, at 20%, represents an arbitrary selection of the probability cut off to be used for this class and data set. As discussed above, the probability threshold can be adjusted in case *a priori* information is available or to reduce the number of missed UXO. Below the 20% probability cut off, 1 UXO target was missed and 69 scrap items were identified as UXO (false alarm). To reduce the number of missed UXO, the probability cut off can be reduced to 10 %, allowing detection of the remaining UXO target. The cost of the additional UXO detection is an increase in the number of false alarms: 100 false alarms versus 69 false alarms at the 20% probability cut off. These results represent a large improvement over typical methods (300-500% false alarm rate) and would result in at least a 50% reduction in the number of false alarms. The effects of reducing the probability threshold are summarized in Table 4. The ROC curve for BBR 2 classified using two classes is shown in Figure 10.

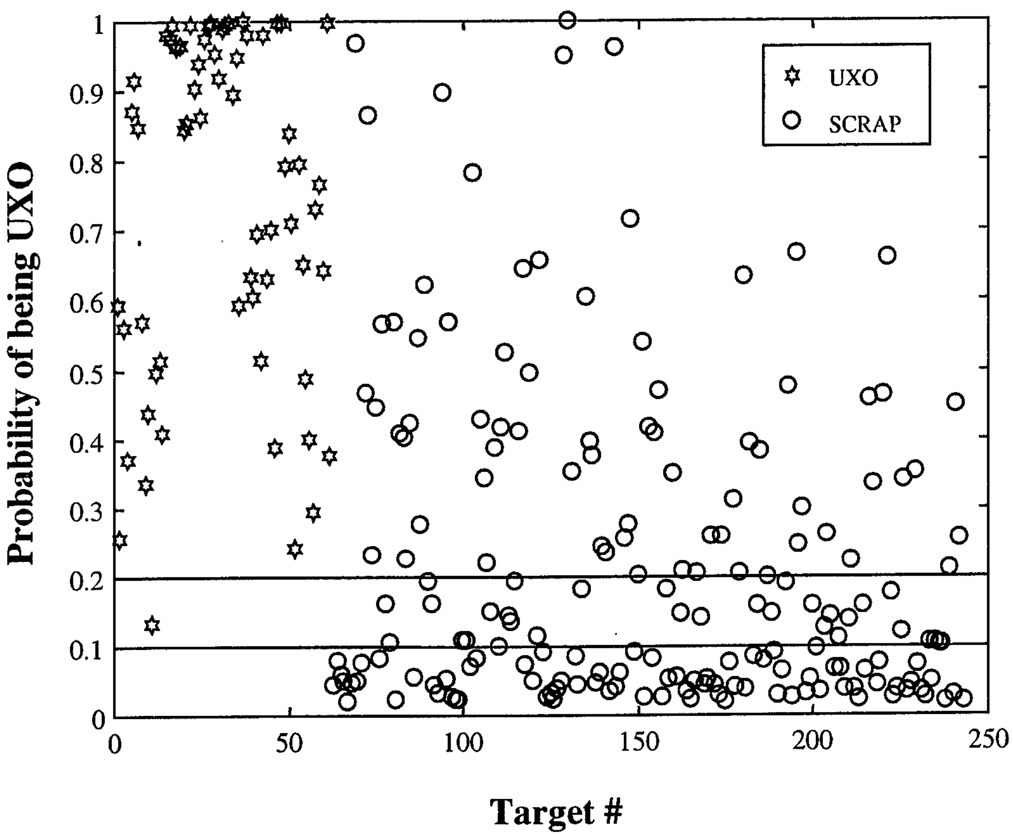

Figure 9. Probability of being UXO versus target number for the two class problem in the BBR 2 data set. The first 62 targets are UXO

Table 4. Summary of UXO Miss Rates and False Alarms for the two class problem

Class	Probability Cut off (%)	# UXO Misclassified	UXO Miss Rate %	# False Alarms	False Alarms (%)
UXO	10	0	**0.0**	100	**55.2**
UXO	20	1	**1.6**	69	**38.1**

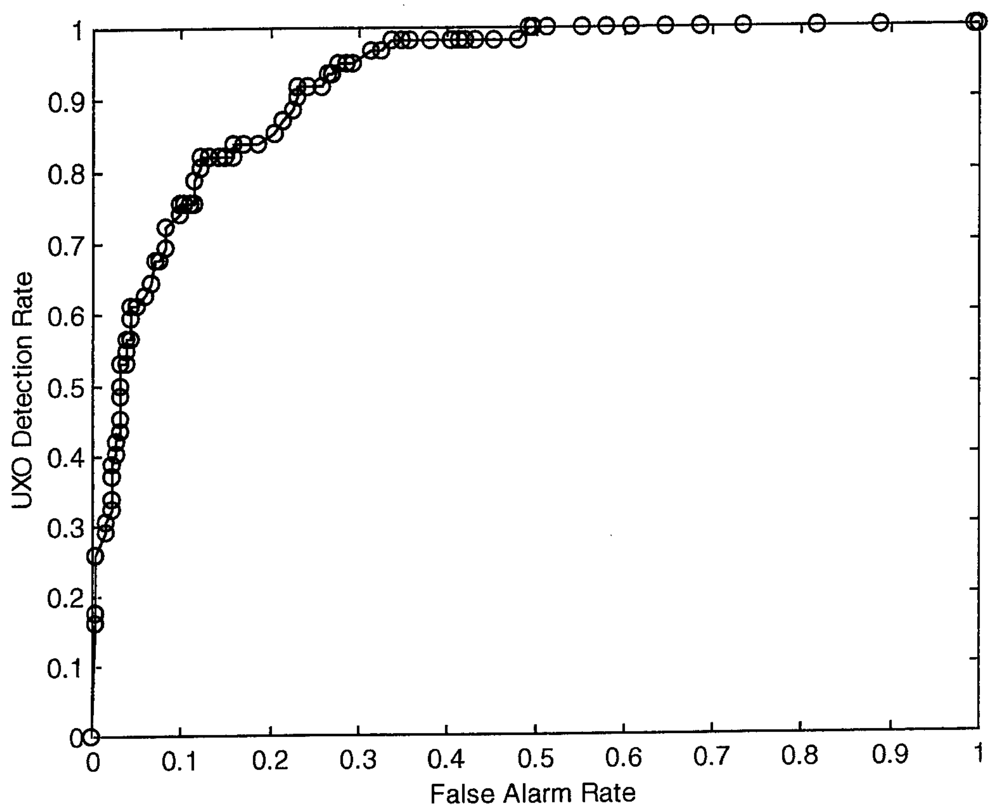

Figure 10. Receiver operator characteristic curve for BBR 2

BBR 2 Classification (4 Class Problem)

The overall results from the single, five and six parameter patterns and representative results from the two, three, and four parameter patterns are given in Table 5. The UXO miss rate and false alarm rate using all parameters were 29.0 % and 27.1 % respectively, corresponding to 18 UXO and 49 scrap targets missed. The parameters found to be most important (causing the greatest increase in UXO miss rate) in the tests using five-parameter patterns were inc > siz > fit > dep > azi = mom. The parameter fit is expected to improve the performance when excluded because it is not based on any

Table 5. *MTADS* parameter combinations and overall PNN cross validation results for BBR 2 Air Base data set using four classes (2.75" War heads (WH), M38 bombs, SCAR rockets, and Scrap

Parameter Combination						UXO	FALSE	# UXO	# Scrap
1	2	3	4	5	6	Miss Rate (%)	Alarm Rate (%)	Missed	Missed
dep	-	-	-	-	-	59.7	14.9	37	27
-	siz	-	-	-	-	41.9	38.7	26	70
-	-	mom	-	-	-	25.8	97.2	16	176
-	-	-	inc	-	-	40.3	73.5	25	133
-	-	-	-	azi		56.5	88.4	35	160
-	-	-	-	-	fit	59.7	75.7	37	137
-	siz	-	inc	-	-	19.4	30.4	12	55
-	-	mom	inc	-	-	24.2	30.4	15	55
dep	-	-	inc	-	-	53.2	34.3	33	62
-	siz	mom	-	-	-	43.5	38.1	27	69
-	-	mom	-	-	fit	51.6	22.1	32	40
-	-	-	-	azi	fit	61.3	69.1	38	125
dep	siz	-	inc	-	-	40.3	12.2	25	22
-	siz	mom	inc	-	-	22.6	30.4	14	55
-	siz	-	inc	azi	-	37.1	13.8	23	25
-	-	-	inc	azi	fit	56.5	51.9	35	94
dep	siz	mom	-	-	-	30.6	19.3	19	35
-	-	mom	-	azi	fit	37.1	38.7	23	70
-	siz	-	inc	azi	fit	30.6	22.1	19	40
dep	siz	mom	inc	-	-	48.4	11.6	30	21
-	siz	mom	inc	azi	-	33.9	16.6	21	30
dep	siz	-	inc	azi	-	29.0	19.3	18	35
-	siz	mom	-	azi	fit	51.6	19.9	32	36
-	siz	mom	inc	azi	fit	33.9	22.7	21	41
dep	-	mom	inc	azi	fit	38.7	19.9	24	36
dep	siz	-	inc	azi	fit	32.3	23.2	20	42
dep	siz	mom	-	azi	fit	45.2	24.3	28	44
dep	siz	mom	inc	-	fit	32.3	22.1	20	40
dep	siz	mom	inc	azi	-	35.5	19.3	22	35
dep	siz	mom	inc	azi	fit	29.0	27.1	18	49

Table 6. Summary of individual class miss rates (%) for representative parameter combinations

Parameters	2.75 WH	Miss Rate (%) M38	SCAR 2.25	Scrap	Overall UXO
mom inc	57.1	23.8	51.9	40.3	43.6
siz inc	28.6	38.1	44.4	23.2	38.7
dep siz inc	28.6	9.5	33.3	27.6	24.2
dep siz mom inc azi	42.9	4.8	51.9	24.9	33.9
dep siz mom inc azi fit	42.9	4.8	44.4	25.4	24.2

physical parameters of the target being identified. However, in this case it had a detrimental effect, perhaps due to better modeler fits on UXO versus scrap at this site. The best single parameter for overall prediction was siz with a UXO miss rate of 41.9 % and a false alarm rate of 28.7. The use of fit alone resulted in the largest classification errors: 59.7 % and 75.7 % for the UXO miss rate and false alarm rate respectively. The best overall classifications were achieved for the three-parameter sets: [siz, inc, azi] and [siz, mom, inc]. Using only two parameters as the input patterns, siz and inc, was the combination that produced the best UXO miss rate, 19.4 %, and false alarm rate, 30.4 %, which correspond to 12 UXO and 55 scrap targets missed. The best UXO detection was obtained with the three-parameter pattern containing siz, mom, inc. The UXO miss rate was 22.6 % and the false alarm rate was 30.4 %.

Shown in Figure 11 are plots of the PNN CV predicted probability of being 2.75" Warheads, M38 bombs, SCAR rockets, and scrap for each of the 243 patterns in the BBR 2 data set using three parameters (dep siz inc). The best results are observed for the M38. The solid, horizontal line in each UXO plot represents an arbitrary selection of the probability cut off threshold to be used for this class and data set. As discussed above, the probability threshold can be adjusted in case *a priori* information is available or to reduce the number of missed detections. However, in several cases, missed detections were predicted with very low probabilities of being UXO (< 40 %). These cut off lines were drawn with the intent to prevent the missed detection of UXO at the expense of false alarms. Fortunately, the majority of scrap items cluster close to zero in the UXO probability plots thus minimizing the number of false alarms at lower probability cut off values. A summary of the missed detections and false alarm rates is given in Table 7.

The misclassifications and low probabilities occur because no other UXO patterns in the class have similar MAG model outputs. In the warhead class, the four targets that had low probabilities were target numbers 2, 4, 9, and 11. Examining the parameters

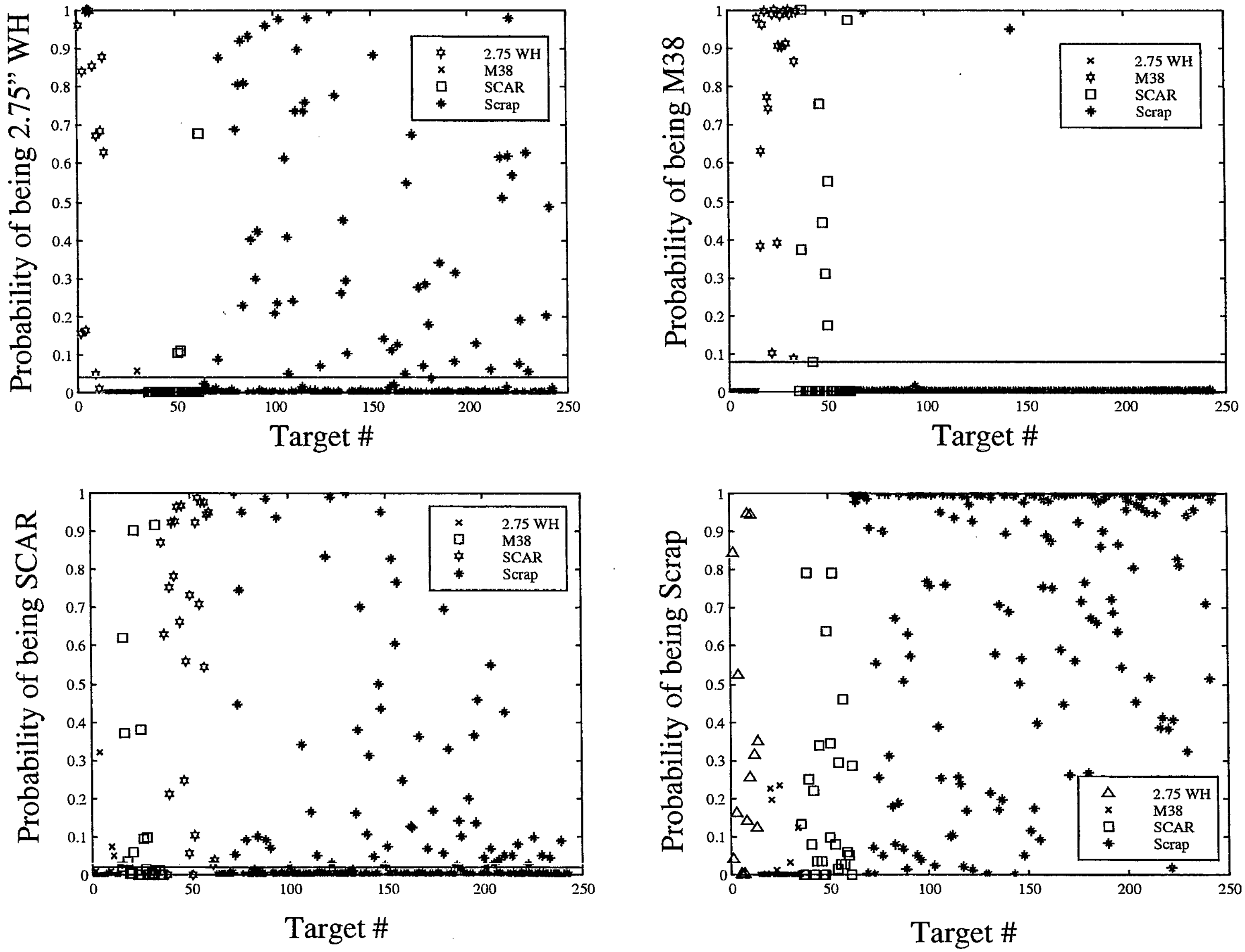

Figure 11. Probability of being UXO as a function of target # for the three UXO classes and Scrap in the data set. The first 62 targets are UXO.

shows that target numbers 2 and 4 had low dep values, 0.04 and 0.08 respectively compared with an average dep value for the others of 0.32 ± 0.19. All of the misclassifications were assigned to the scrap class by the PNN. In the M38 class, four targets had low probabilities of which three were misclassified: target numbers 16, 22, and 33. Target # 22 had a high dep value 0.62 and a low inc value, 9, compared with the average of the others: 0.46 ± 0.13 and 42.2 ± 23.5. The remediation comment for this target was "M38 deformed". Target # 33 had a larger siz, 0.30 compared with 0.21 ± 0.03 for the average of the others. The remediation comment for this target was "M38 + SCAR". For the SCAR class, there were eight targets with low probability that were misclassified: target numbers 38, 39, 47, 49, 51, 52, 61, 62. Targets number 38 had a high siz and inc, 0.23 and 37 respectively compared with the average values for the others, 0.15 ± 0.06 and 13.2 ± 8.8. Target 39 and 49 had low inc values, 0 and 2 respectively. Targets 51 and 62 had high inc values, 50 and 33 respectively. In addition, targets 52 and 62 had low dep values, both 0.06 compared with the average value of the other targets, 0.15 ± 0.06.

In the eventual application of this technology, larger data sets comprised of UXO and scrap from many sites will be used to prevent this situation from occurring. An extensive examination of the effects of using different combinations of modeler output parameters on the classification performance of a PNN has been completed. The results obtained in this study are probably data set dependent and may vary according to the type of UXO and scrap encountered, the amount of scrap present, soil type, and other geological effects.

Table 7. Summary of missed detection and false alarm rates for the 4-class problem

Class	Probability Cut off (%)	# UXO Misclassified	UXO Miss Rate (%)	# False Alarms	False Alarms (%)[a]
2.75" Warheads (WH)	4	1	**7.1**	62	**37.1**
M38 Bombs	8	0	**0.0**	10	**6.3**
SCAR	2	2	**7.4**	74	**48.1**

[a] Percentage of scrap and UXO other than the type in question

Improved Classification with Fit Parameter Selection

Improvements in PNN classification can be obtained through the use of data selection. The selection of targets based upon the quality of the modeler's fit can provide some discrimination between low and high quality data. This approach can be used to construct a better training set or to select those targets whose fit parameter is low enough that positive identification is unlikely. The effects of retaining only those targets with a fit parameter above a specified cut off threshold were examined for the two and four class problems.

BBR 2 Classification (2 Class Problem)

The results of PNN classification with varying numbers of targets removed based upon the fit parameter are given in Figure 12. The results of PNN-CV on parameters 1:5 (dep siz mom inc azi) shown in Figure 12 indicates that the best overall classification can be obtained using a fit parameter cut off of 0.96. Using only targets with a fit parameter > 0.96 results in cross-validation miss rates (%) of 25.6 and 7.5 for UXO and scrap respectively. Figure 13 a and b show that at the selected cut off (0.96), 47 UXO targets out of 62 total UXO targets (76%) were kept in the data set. Similarly, 93 scrap targets out of 181 total scrap targets (51%) were kept in the data set. This represents a compromise between the number of targets removed and the classification performance. It can be seen in Figure 12, that the performance of both the UXO and scrap classes improved somewhat inconsistently until the fit parameter cut off was ~ 0.96.

The combination of the best parameters and the fit parameter cut off did not result in further enhancement of performance. Using the combination [dep siz inc] and a fit parameter cutoff of 0.96 resulted in a UXO miss rate of 17.0% and a scrap miss rate of 8.6 %. For UXO detection this result is poorer than the best parameter selection, but better than the fit cut off selection. While for scrap detection this result is an improvement over the best parameter selection result and marginally worse than the fit cut off selection result.

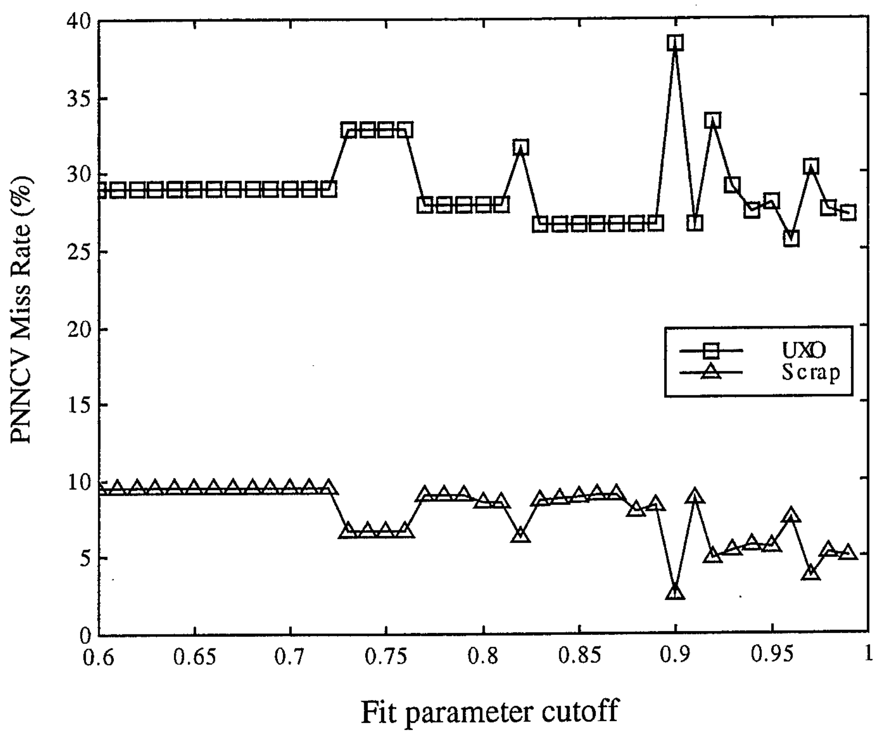

Figure 12. PNN cross-validation miss rate (%) versus fit parameter cut off for the 2-class problem

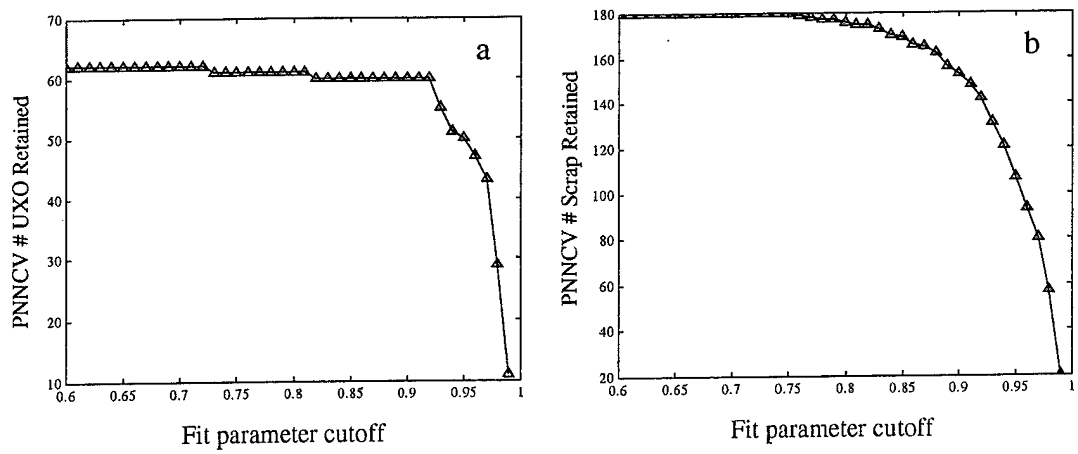

Figure 13. PNN cross-validation results as a function of fit parameter cut off. a) # UXO retained, b) # Scrap retained

BBR 2 Classification (4 Class Problem)

The results of PNN classification with varying numbers of targets removed based upon the fit parameter are given in Figure 14. The results of PNN-CV on parameters 1:5 (dep siz mom inc azi) shown in Figure 14 indicate that the best overall classification can be obtained using a fit parameter cut off of 0.92. Using only targets with a fit parameter > 0.92 results in cross-validation miss rates (%) of 25.0, 4.8, 48.1, and 20.4 for 2.75 warheads, M38 bombs, SCAR rockets, and scrap respectively. Figure 13 a and b shows that at the selected cut off (0.92), 60 UXO targets out of 62 total UXO targets (97 %) were kept in the data set. Similarly, 142 scrap targets out of 181 total scrap targets (79 %) were kept in the data set. It can be seen in Figure 14, that the classification performance of all UXO classes (2.75 warheads, M38 bombs, and SCAR rockets) improved or remained constant with increasing fit parameter cut off (up to 0.92), while class 4 (Scrap) classification worsened slightly.

The combination of the best parameters and the fit parameter cut off did not result in further enhancement of performance. Using the combination [dep siz inc] resulted in a UXO miss rate of 25.0%, 19.0%, 37.0% for 2.75 warheads, M38 bombs, and SCAR rockets, respectively, and a scrap miss rate of 21.1%. For 2.75 warheads, the classification result was the same, while the classification was poorer for M38 bombs. There was some improvement in the classification of SCAR rockets, but a slight increase in the scrap miss rate.

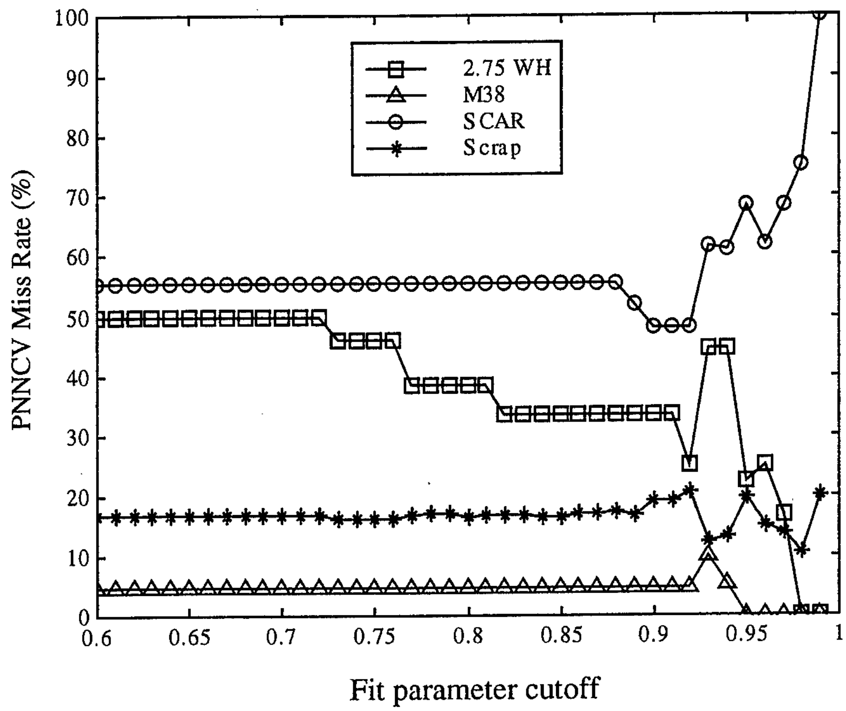

Figure 14. PNN cross-validation miss rate (%) versus fit parameter cut off for the four-class problem

Former Buckley Air Base

The Buckley data set (Buckley Air Base, Bombing Target #2, Section A5) was investigated to determine the ability of a PNN to distinguish UXO from scrap at this site. For PNN classification, the Buckley data set tested contained MAG physics-based modeler outputs from 392 buried objects that had been remediated. A 392 × 6 data matrix was generated and evaluated as both a two- and five-class problem. The pattern vectors were subdivided into two categories or classes, UXO and Scrap for the data set classification labeled Buckley1 and into five classes for the data set classification labeled Buckley2. The Buckley2 data set consisted of 69 M38, 8 SCAR rockets, 7 M69 bombs, 30 MK23 practice bombs and 6 M100 series fuses (in the same class), while the 272 scrap primarily consisted of OE scrap and scrap metal. A few (target # 292, 339, 340) of the targets did not have modeler outputs in the table and three others had descriptions which were unclear and were therefore left out of the data set.

The data sets used for classification testing were prepared by selecting those targets with the descriptions listed above from the modeler output and truth tables for this site. The PNN was used to discriminate either two classes or four classes of objects (i.e., differentiate four UXO types from each other and scrap). The parameters used in this work were derived from MAG data. The Buckley data set represents a challenge to the PNN classification routines using modeler outputs for the discrimination of UXO from scrap.

Data Set Characterization

An examination of the data set using PCA and non-linear mapping was undertaken to understand the clustering and overlap of the UXO classes and scrap in the data set. The scores from the first two factors, or principal components, for the Buckley data set are shown Figure 15. Significant overlap between the classes can be seen in this plot. However, there is some separation between the classes indicating differences in the modeler outputs for each class. A plot of the data in two dimensions generated by non-linear mapping is shown in Figure 16. An examination of Figure 16 reveals that the scrap class is overlapped with the MK23 class. Based upon the degree of separation between

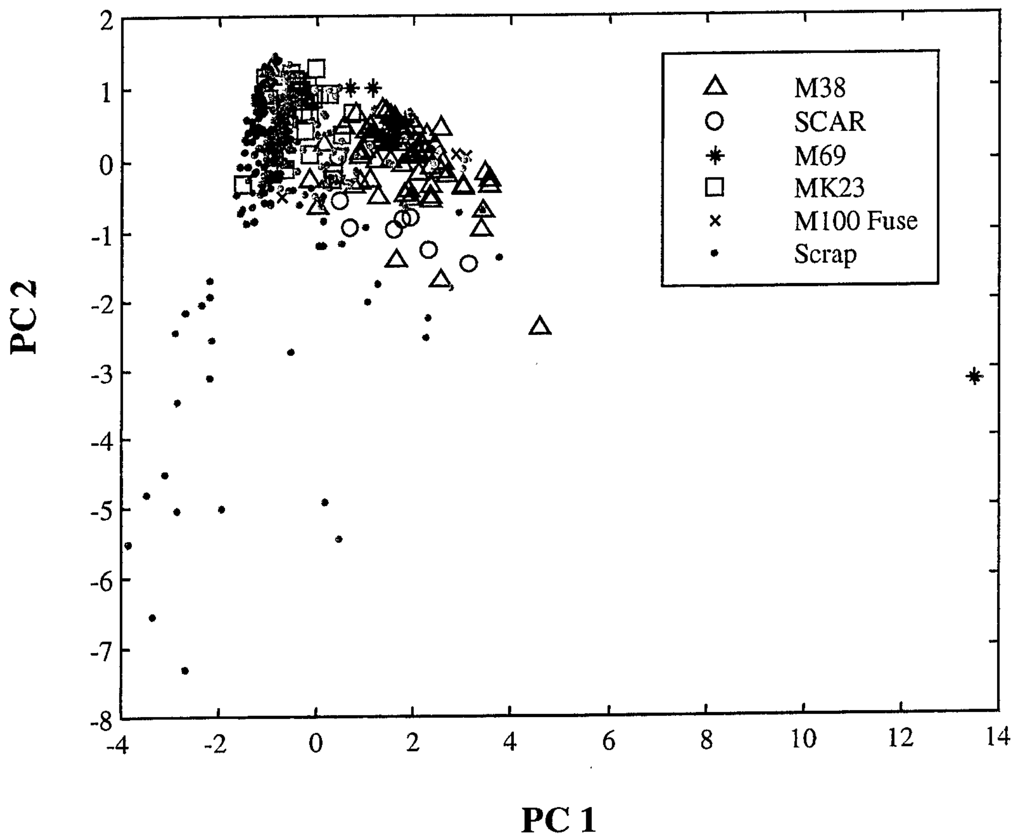

Figure 15. PCA scores plot of the Buckley data set

the classes seen in both PCA and non-linear mapping, accurate classification of this data set should be challenging. One target (target # 84) is an outlier in PCA and non-linear mapping found at 13.5, -2.9 and 14.0, -9.0 respectively. The description in the remediation list was incendiary cluster bomb and the source of the error was likely the moment parameter which had a value of 32.3. This moment is very high for such an item: the average of others in its class was 1.5 ± 0.5.

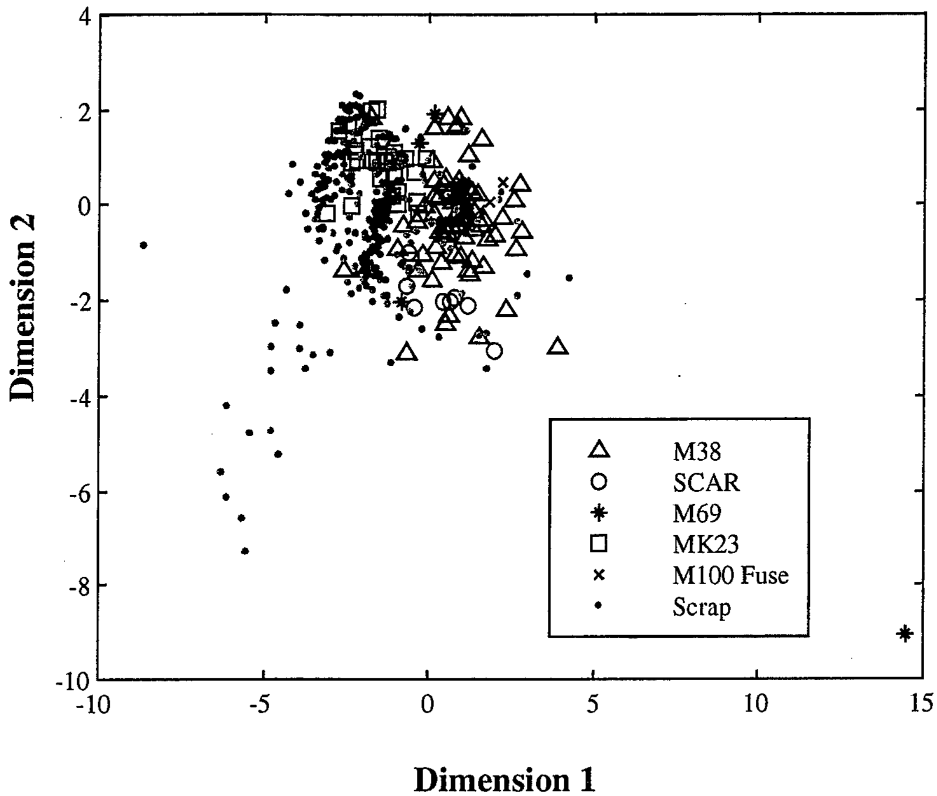

Figure 16. Non-linear map plot of the Buckley data set

Cross-Validation Performance

PNN classification performance was examined using leave-one-out-cross-validation (CV). In this work, the PNN returned either four or two values for each pattern: the probability of being one of the three UXO types and the probability of being scrap or simply UXO or scrap. Each pattern was assigned to the category having the highest probability. In a real-world scenario, this probability threshold can be adjusted for a particular site using *a priori* information regarding the types and relative number of buried objects.

To determine which MAG model parameters were most important and to gain insight into the PNN classification, the effect of various model parameters were studied. PNN CV performance was determined for all possible combinations of one, two, three, four, five, and six MAG model parameters. The UXO miss rate (missed detection) is defined as the ratio of the number of UXO classified as scrap to the total number of UXO targets classified. The false alarm rate is defined as the ratio of the number of scrap classified as UXO to the total number of scrap classified.

Buckley2 Classification (Five-Class Problem)

The overall results from the single, five and six parameter patterns and representative results from the two, three, and four parameter patterns are given in Table 8. The UXO miss rate and false alarm rate using all parameters were 34.2 % and 17.3 % respectively, corresponding to 41 UXO and 47 scrap targets missed for an overall correct classification of 78 % of the data set. The parameters found to be most important (causing the greatest increase in UXO miss rate) in the tests using five-parameter patterns were dep = inc > siz > fit > azi. One of the parameters, azi had a beneficial effect on the UXO miss rate when left out of the pattern. The omission of the parameter, mom, had a beneficial effect on the classification of this data set which is different from its effect when omitted from the Badlands data set (no effect).

There was no single best parameter for overall prediction: all had poor classification or fell prey to over training as indicated by the superscript "a" in Table 8. The best results for UXO detection were obtained with three paramters [dep siz inc], and five parameters [dep siz mom inc azi] and [dep siz inc azi fit]. The UXO miss rate for three parameter combination was 29.2 % and the false alarm rate was 24.3 %. The individual miss rate percentages for each class are given in Table 9 for the best parameter combination and compared with the result obtained using all parameters.

Table 8. *MTADS* parameter combinations and overall PNN cross validation results for Buckley Air Base data set (5 class problem)

Parameter Combination 1	2	3	4	5	6	UXO Miss Rate (%)	False Alarm Rate (%)	# UXO Missed	# Scrap Missed
dep	-	-	-	-	-	62.5	33.1	75	90
-	siz	-	-	-	-	23.3	34.9	28	95 [a]
-	-	mom	-	-	-	0.0	4.4	0	12 [a]
-	-	-	inc	-	-	75.0	63.6	90	173
-	-	-	-	azi		65.0	76.8	78	209
-	-	-	-	-	fit	83.3	40.4	100	110
-	siz	-	inc	-	-	40.8	27.2	49	74
-	-	mom	inc	-	-	48.3	27.2	58	74
dep	-	-	inc	-	-	43.3	37.5	52	102
-	siz	mom	-	-	-	45.8	27.6	55	75
-	-	mom	-	-	fit	46.7	33.1	56	90
-	-	-	-	azi	fit	68.3	50.7	82	138
dep	siz	-	inc	-	-	29.2	24.3	35	66
-	siz	mom	inc	-	-	41.7	27.2	50	74
-	siz	-	inc	azi	-	39.2	28.3	47	77
-	-	-	inc	azi	fit	54.2	47.4	65	129
dep	siz	mom	-	-	-	43.3	30.1	52	82
-	-	mom	-	azi	fit	50.8	30.1	61	82
-	siz	-	inc	azi	fit	41.7	24.3	50	66
dep	siz	mom	inc	-	-	31.7	24.6	38	67
-	siz	mom	inc	azi	-	41.7	27.9	50	76
dep	siz	-	-	azi	fit	40.0	22.1	48	60
-	siz	mom	-	azi	fit	46.7	29.8	56	81
-	siz	mom	inc	azi	fit	40.0	21.7	48	59
dep	-	mom	inc	azi	fit	35.8	21.7	43	59
dep	siz	-	inc	azi	fit	30.8	19.1	37	52
dep	siz	mom	-	azi	fit	40.0	21.3	48	58
dep	siz	mom	inc	-	fit	32.5	22.1	39	60
dep	siz	mom	inc	azi	-	35.0	25.0	42	68
dep	siz	mom	inc	azi	fit	34.2	17.3	41	47

[a] Good result is due to over training not intrinsic properties of the data and represents an anomaly. Over training indicated by large sigmas: 1.35 and 8.40 respectively compared with average of others: 0.34 ± 0.10

Table 9. Best Class Miss Rate Percentages

Parameters	Miss Rate (%)* Class 1	Class 2	Class 3	Class 4	Class 5	Overall UXO Miss Rate (%)
siz inc	40.6	50.0	57.1	36.1	26.8	40.8
mom inc	42.0	50.0	100.0	50.0	27.2	45.8
siz mom	47.8	75.0	57.1	33.3	27.6	48.3
dep siz inc	23.2	25.0	42.9	36.1	24.3	29.2
dep siz mom inc	24.6	37.5	42.9	36.1	24.3	31.7
All parameters	26.1	25.0	71.4	44.4	17.3	34.2

* Class 1 are M38, class 2 are SCAR, class 3 are M69 bombs, class 4 are MK23 practice bombs and M100 series fuses, and class 5 are scrap.

	M38	SCAR	M69	MK23& M100 fuse	SCRAP	Classification Correct (%)
M38	53	7	4	2	3	76.8
SCAR	0	6	0	0	2	75.0
M69	2	0	4	0	1	57.1
MK23& M100 fuse	3	0	1	23	9	63.9
SCRAP	17	10	7	32	206	75.7

Figure 17. Confusion matrix showing the individual misclassifications in each class for the 5 class problem using the 3 parameters [dep siz inc] found to be one of the most important combinations for good classification

The PNN-CV classification results are shown in Figure 17 for each class using one of the better parameter combinations: [dep siz inc]. The results are displayed in a confusion matrix format to illustrate the misclassifications. It should be noted that classification percentages listed in the figure are for the individual classes. If one considers UXO targets misclassified as other UXO, the percentage increases for M38, M69, and MK23 & m100 fuses: 95.6 %, 85.7 %, 75.0 % respectively.

Shown in Figure 18 is a plot of the PNN CV predicted probability of being one of the four UXO classes for each of the 392 patterns in the Buckley data set using just three MAG parameters (dep, siz, inc). The upper solid, horizontal line represents an arbitrary selection of the probability cut off threshold (20 %) to be used for this data set. As discussed above, the probability threshold can be adjusted in case *a priori* information is available or to reduce the number of missed detections. However, in several cases, missed detections were predicted with very low probabilities of being UXO (< 5 %). These misclassifications occur because no other UXO patterns in the class have similar MAG model outputs. Using a 20 % cut off, 28 UXO were missed (23 %) with a false alarm rate of 9 %. Further improvements in UXO detection can be obtained by lowering the probability threshold further. At 10 % cut off, 21 UXO were missed (18 %) with a false alarm rate of 13 %. Finally, at 5 % cut off, 15 UXO were missed (13 %) with a false alarm rate of 17 %.

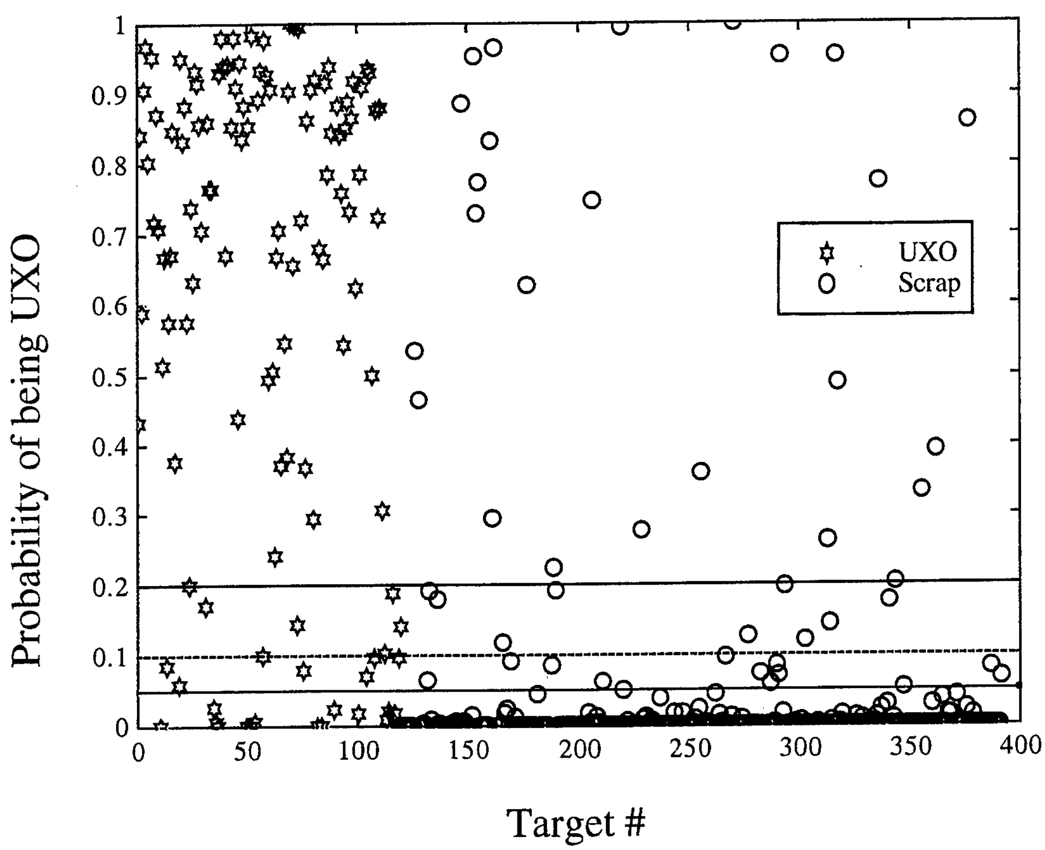

Figure 18. Probability of being a UXO (four UXO classes) versus target number. The first 120 targets are UXO.

Buckley 1 Classification (2 Class Problem)

Representative results from the two, three, four and five parameter patterns are given in Table 10. The UXO miss rate and false alarm rate using all parameters were 12.5% and 14.0% respectively, corresponding to 15 UXO and 38 scrap targets missed. Using fewer parameters did not benefit classification of UXO. Some benefit was seen for scrap classification using the two parameter combinations. Using only two parameters as the input patterns, [siz inc] produced 19.2% UXO miss rate, and 12.1% false alarm rate. The increase in the UXO miss rate with reduced parameters is markedly different from the other data sets studied where the classification performance of the two class problem remained the same or improved.

Table 10. *MTADS* parameter combinations and PNN cross validation results for Buckley Air Base data set (2 Class Problem)

Parameters					Misclassification rate UXO (%)	Scrap (%)
siz	inc				19.2	12.1
mom	inc				34.2	7.4
siz	mom				30.0	12.9
dep	siz	inc			19.2	15.1
dep	siz	mom	inc		19.2	15.1
dep	siz	mom	inc	azi	18.3	15.1
All parameters					12.5	14.0

The probability of being a UXO is shown in Figure 19 for all 392 targets in the Buckley data set. These probabilities were generated using the parameter combination found to produce the best classification results: [dep siz inc]. The solid, horizontal line represents an arbitrary selection of the probability cut off threshold (30 %) to be used for this class and data set. As discussed above, the probability threshold can be adjusted in case *a priori* information is available or to reduce the number of missed UXO. Below the 30 % probability cut off, marked by the upper solid horizontal line, 11 UXO targets (9.2 %) were missed and 70 scrap items (25.7 %) were identified as UXO (false alarm). The identities of the misclassified UXO targets are given in Table 11 with the possible cause of misclassification. The outlier (target # 84, with mom = 32.3) was correctly classified in this case because mom was not used. To reduce the number of missed UXO, the probability cut off can be reduced to 20 %, allowing detection of an additional 4 UXO. The cost of the additional 4 UXO detections is an increase in the number of false alarms: 92 false alarms versus 70 false alarms at 30 % probability cut off. These amount to a UXO miss rate of 5.8 % and a false alarm rate of 33.8 %. The ROC curve for the Buckley data set can be seen in Figure 20.

Table 11. Buckley 2 class problem using [dep siz inc] misclassified targets and possible cause

Target #	Description	Possible Misclassification Cause
52	M38	low dep, siz
54	M38	low siz
82	AN-M69 bomblet cluster	low inc
90	MK23	low inc
104	MK23 (borderline)	low siz
107	MK23	low dep
108	MK23	low dep
112	MK23	low siz
114	MK23 Practice bomb	low dep
115	100 Series fuse	low dep, siz

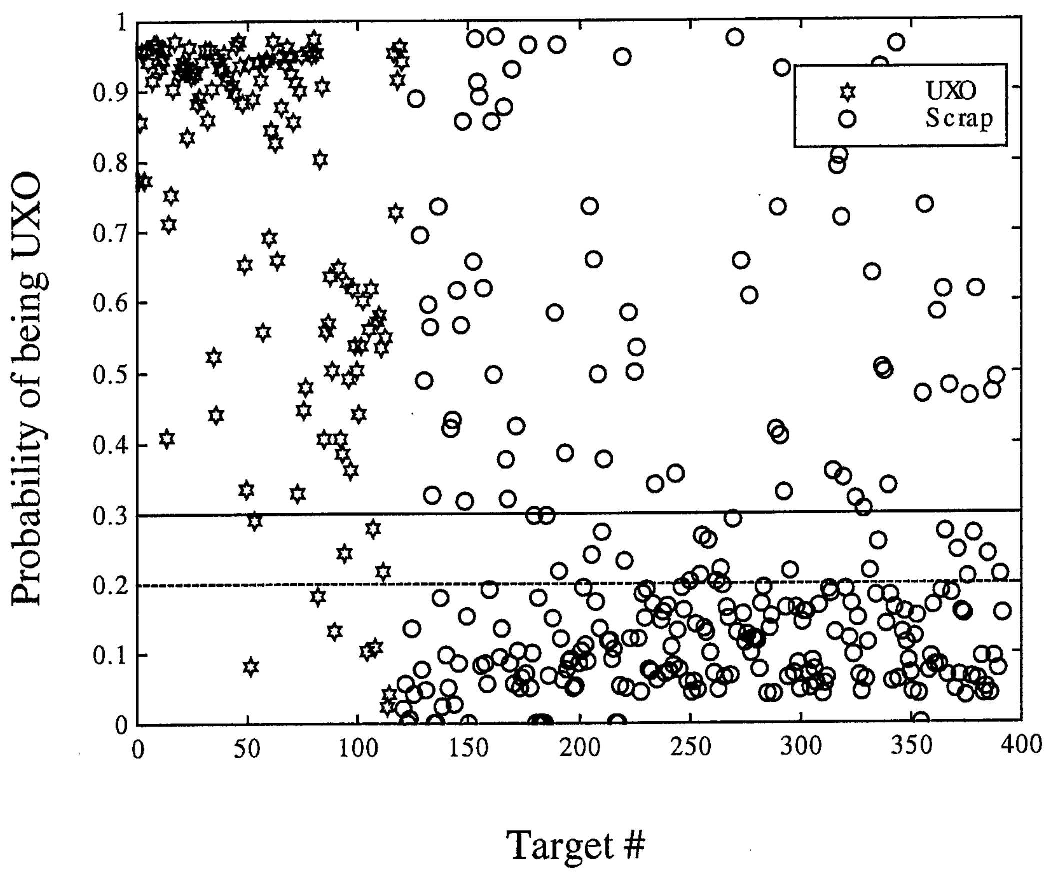

Figure 19. Probability of being UXO versus target number for the two class problem in the Buckley1 data set using [dep siz inc]. The first 120 targets are UXO

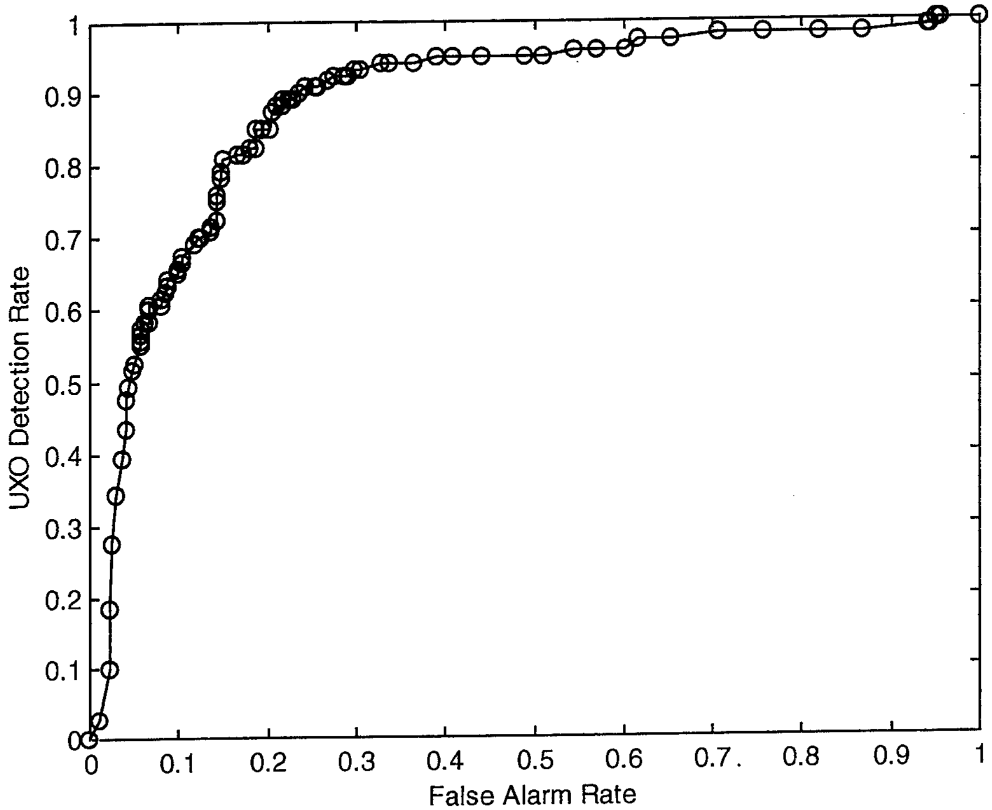

Figure 20. Receiver operator characteristic curve for Buckley

An extensive examination of the effects of using different combinations of modeler output parameters on the classification performance of a PNN has been completed. The results obtained in this study are probably data set dependent and may vary according to the type of UXO and scrap encountered, the amount of scrap present, soil type, etc. This is verified by comparing the results obtained using the different data sets. The improvement in miss rate was 3.4 % for the Buckley2 data set. The overall improvement in the UXO miss rate for the BBR 1 data set was only 2 % and there was no false alarm penalty for the improved UXO detection capability. For the two class problem in BBR 2, there was a greater improvement (11 %) in UXO miss rate, with only a small false alarm penalty (0.6 %). In the Buckley data set, classification was adversely effected by parameter reduction and selection in the 2 class problem and the best overall performance obtainable was with all parameters using two classes. However, reasonable classification could be achieved using a similar parameter selection as that used for the other data sets [dep siz inc] or [siz inc].

Analysis of M38 Targets from BBR1 and BBR 2

Principal component analysis was performed on a data set prepared from M38 targets measured and remediated at BBR 1 and BBR 2 to determine if the targets observed at different locations at this site clustered similarly. All of the scrap items from both sites were included in the analysis. One can see in the PCA plot shown in Figure 21 that the BBR1 and BBR 2 M38 targets are overlapped and separated from the scrap found at both locations. This indicates that either data set could be used as a training

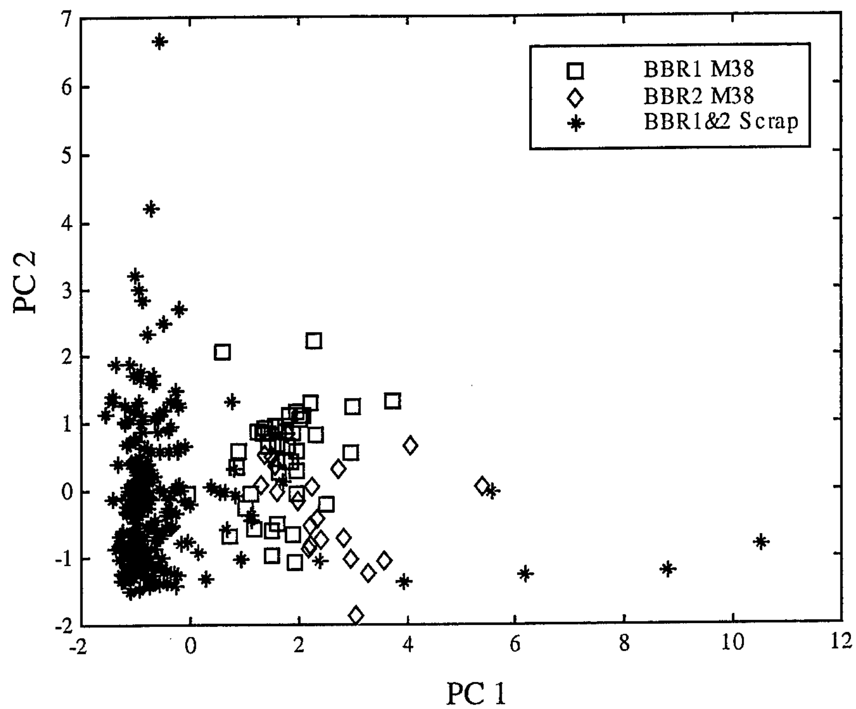

Figure 21. Principal component analysis of M38 targets from BBR 1 and BBR 2. Two principal components account for 61.9 % of the variance

set to predict the M38 targets in the other. The ability to use data from one location to predict items at another location is of utmost importance to the development of the PNN. Ideally, training data from one location could be used at least as a starting point for an entirely different site. In an effort to test this, the entire BBR 2 data set was used to train the PNN and the BBR1 data set was used in prediction. The parameters used were those that gave the best results in PNN-CV for BBR 2: [dep siz inc]. For the two classes in BBR1, M38 and scrap, the UXO miss rate was 4.5 % and the false alarm rate was 34.9 %, using a 40 % probability cutoff. A plot of the probability of being an M38 versus target number is shown in Figure 22. There are only two UXO targets with probabilities below 40 %. These targets, 19 and 34, were also misclassified during the PNN-CV of the BBR1 data set. The ROC curve for this prediction set is shown in Figure 23.

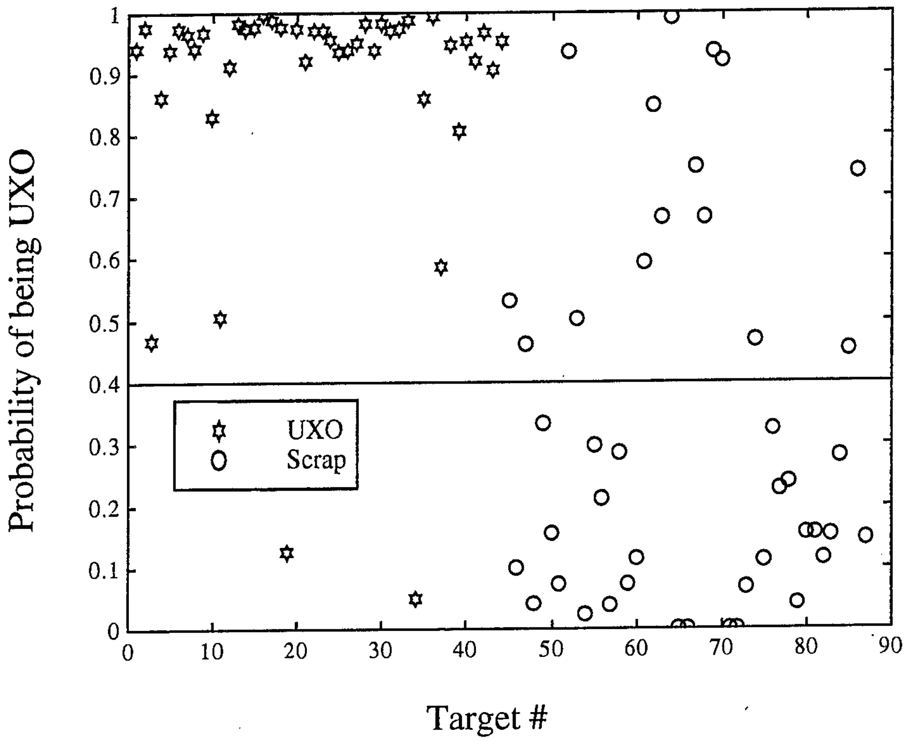

Figure 22. Probability of being M38 versus target number for BBR 2 training set with BBR 1 prediction set

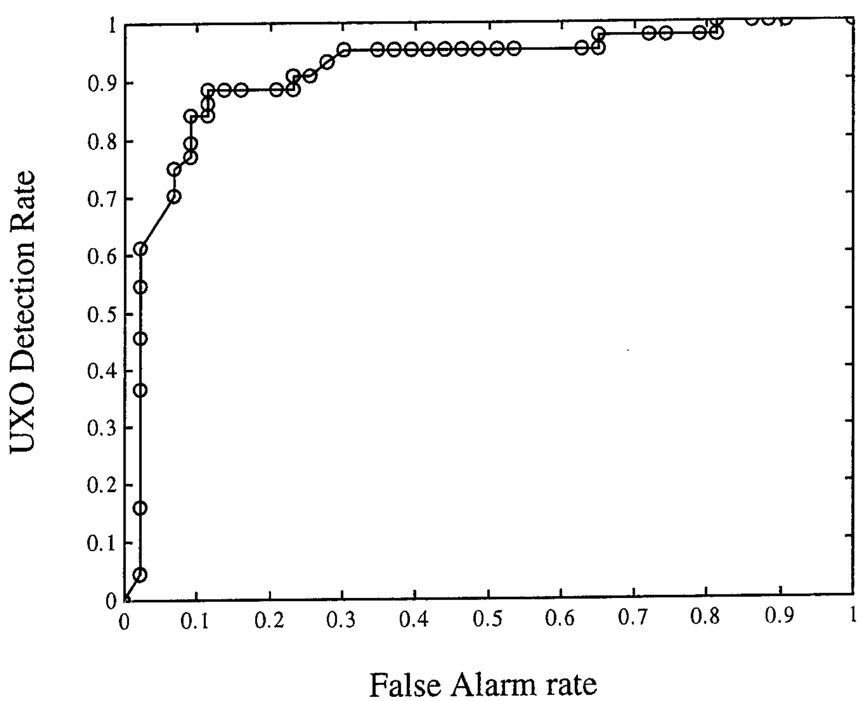

Figure 23. Receiver operator curve for BBR 2 training set with BBR 1 prediction set

CONCLUSIONS

This report demonstrates the usefulness of multivariate methods for identifying UXO in the presence of scrap and other clutter. In particular, the methods have been used to select the optimal set of MAG modeler parameters to achieve the best classification results for three different UXO surveys. Using the Badlands *Bull's eye* Target 1, 94 % of the targets are correctly identified, and 86 % correct classification was achieved at the more complex Target 2 site. The Buckley site was the most difficult using only the MAG modeler outputs due to the small size of the UXO targets and only 84 % of the targets are correctly identified. The ability to use the classification model from one site on data from another was demonstrated for the two Badlands Test Sites. The PNN classifier was trained using the Badlands Target 2 dataset, and was able to correctly predict 93 % of the targets at Bull's eye Target 1.

Three *MTADS* data sets have been evaluated and classification performance tested using a PNN. Several approaches to improve the performance of the classification have been investigated. These include variable or parameter selection based upon cross-validation testing, probability threshold reduction, and data exclusion via fit parameter cut off. Of these approaches, parameter selection and probability threshold reduction were found to be the most useful. The variables found to be most important were siz, inc, dep, and mom in order of importance. For BBR1, [siz, inc] were the favored combination; for BBR2, [siz, inc, azi] were the variables that produced the best results, with [dep, siz, inc] being nearly as effective. For the Buckley data set, the most important variables were [dep siz inc]. For the BBR2 and Buckley data sets, two classification types were attempted: 2 class (UXO and scrap) and multi-class (UXO types and scrap). In both cases, better classification (less UXO missed) was obtained by defining the problem in terms of two classes.

For BBR 1, the improvement using variable selection was 2.3 %, while no improvement was found using probability threshold reduction. At BBR 2, there was additional 11.3 % improvement in classification using variable selection and an 8.1 % to 11.3 % improvement over that using probability threshold reduction. There was no improvement at the Buckley site using variable selection and a 13.4 % improvement using probability threshold reduction (for two class problem with [dep siz inc]).

It should be noted that the fit parameter cut off would only be useful for training set selection. If the fit parameter was too low, then the target would automatically be remediated otherwise the PNN would classify the target. The performance benefits seen using the fit parameter cut off were inconsistent and no clear trend in the performance as a function of fit parameter was detectable. Furthermore, the combination of the fit parameter cut off and variable selection did not generally have a beneficial synergistic effect.

A summary of the classification results for all three datasets investigated is given in Table 12. As the probability threshold is decreased, the number of UXO missed detections decreases and the scrap false alarms increases. At BBR 1, placing the probability threshold below 50 % does not permit the correct classification of any additional UXO or scrap targets without an unacceptable increase in false alarms. Improvements were possible at BBR 2 by lowering the threshold from 50 % to 10 %

where none of the UXO were misclassified. At Buckley, a probability threshold of 20 % yielded 7 UXO misclassified. Even with a probability threshold of 10 % three UXO targets were still misclassified while requiring almost all of the scrap to be remediated.

Table 12. Summary of the best UXO and scrap classification rates at various probability thresholds

Dataset	Modeler Parameters	Output Coding[a]	Probability Threshold (%)	UXO Correct	Scrap Correct	Overall Classification (%)
Badlands Target 1	[dep siz inc]	2	50	42/44	40/43	94.3
			b	b	b	b
Badlands Target 2	[dep siz inc]	2	50	49/62	160/181	86.0
			20	61/62	112/181	71.2
			10	62/62	81/181	58.9
Buckley	[dep siz inc]	2	50	97/120	231/272	83.7
			30	109/120	202/272	79.3
			20	113/120	180/272	74.7

[a] Number of classes used in training of PNN

[b] No additional benefits obtained through reduction of probability threshold

The performance of any classification routine, including the PNN, is limited by the separation of the data in multi-dimensional space. The PNN is known for its ability to accommodate and correctly classify multi-modal data sets. It is our recommendation that improvements to the modeler or inclusion of EM data will be needed for better classification of highly overlapping data sets.

Future work will also include a detailed investigation of how well the PNN will perform when trained using data from one site to predict another. The initial results using BBR 1 and BBR 2 presented in this report indicate that this will be possible. Other work to improve the classification performance will include the use of multiple kernel widths (σ) in the PNN. Incorporation of the EM data into these models is expected to improve the classification results.

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